Power Aggregation Business Models, Prices and Consumer Behaviour: An Agent based Modelling Approach

PhD Thesis

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Abstract

UK electricity demand is expected to increase by about 50-100% over the next 30 years, driven primarily by the UK's net zero policy. The addition of renewables, EV's and other low carbon technologies introduces more uncertainty into the system driving the need for flexibility services. These flexibility services can be provided by traditional generators, but EV's, storage, and demand side response are expected to provide a larger share of this. It is evident that domestic customers can provide flexibility services to the system, but modelling their responses, behaviours will be difficult. They are social and emotive actors who exhibit non-stationary behaviours that are difficult to represent and are often ignored or oversimplified. There is therefore a need for an extensible tool to simulate customer interactions with aggregators and system operators. This thesis presents an Agent Based Modelling (ABM) framework that incorporates these behaviours. Customers are represented using behavioural rules using a modified "Agent_Zero" framework. Aggregators are represented as commercial entities selecting appropriate business models for the markets they operate in. Aggregators compete against other aggregators and compete for customers in this simulation.

Aggregators also face new risks in this evolving market that will require valuation and risk control. A real option model of the risk associated with aggregator operation is developed and incorporated into a case study using 55,000 customers, representative of a UK city the size of Dundee or York.

These aspects provide complex behavioural interactions that provides a rich set of outputs. Analysis of the results show that aggregator business models evolve through time and that business model choice is a complex one. Price impacts of emotions/networked social influences are significant (~30-50%). Simulation output can be used as an input into future market designs and provides benefits to different stakeholders including regulators, generators, customers and future aggregators.

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Abbreviations

ABM	Agent Based Model
AC OPF	Alternating Current Optimal Power flow
AIC	Akaike Information Criterion
AOP	Aspect Orientated Programing
API	Application Programming Interface
ARL	Aggregate Responsive Load
AZ	Agent Zero
BAU	Business As Usual
BMRS	Balancing Mechanism Reporting Service
BM	Business model
BS	Black Scholes (Option Model)
CA	Cellular Automata
CAS	Complex Adaptive System
CGCL	Curtailable Generation Curtailable Load
CCGT	Closed Cycle Gas Turbine
CDF	Cumulative Probability Density Function
CF	Cashflow or Capacity Factor
CGCL	Curtailed Generation Curtailed Loads
CP	Clearing price
CPX	Capital Expenditure (Costs)
Cshflow	Cashflow
CVaR	Conditional Value at Risk
DA	Day Ahead
DC OPF	Direct Current Optimal Power flow
Depr	Depreciation
DER	Distributed Energy Resources
DG	Distributed Generation
DNO	Distribution Network Operator
DSO	Distribution system operator
DSR	Demand Side Response
ED	Economic dispatch

EMLab	Electricity Market Lab
Eqn	Equation
ESO	Electricity Supply Operator
EV	Electrical Vehicle
FBP	Flow Based Programming
FCM	Fuzzy Cognitive Map
FES	Future Energy Scenarios
FMI	Function Mock Up Interface
FMU	Functional Mock Up Unit
FP	Fixed Price
FSM	Finite state Machine
GO-P2P	Global Observatory on Peer-to-Peer
GPU	Graphical Processing Unit
GSP	Grid Supply Point
GUI	Graphical User Interface
HH	Half hourly
HHI	Herfindahl - Hirschman Index
HLA	High Level Architecture
HR	Heat Rate or Human Resources
IRR	Internal Rate of Return
ISO	Independent system operator
KPI	Key Performance Indicators
kWh	Kilowatt Hour
LA	Learning Automata
LCM	Local Constraint Market
LP	Linear Programming
LSE	Load Serving Entities
LSTM	Long and Short Term Memory
LV	Low voltage
M^3	Metre cubed - volume
MABS	Multi Agent Based systems
MAS	Multi agent system
MC	Marginal cost
MLP	Multi-Layer Perceptron
MMbtu	Million BTU (British thermal units)

MUSCo	Multiple Utilities within Same Contract
MV	Medium voltage
MW	Megawatt
MWh	Megawatt hours
NDM	Naturalistic Decision Making
NIV	Net Imbalance Volume
NN	Neural Network
NPV	Net Present Value
NPV/I	Net Present Value divided by Investment
OCGT	Open cycle gas Turbine
OPF	Optimal Power Flow
OPX	Operating Expenditure (Costs)
ORM	Object Relational Mapping
P&L	Profit and Loss
P2P	Peer to Peer
PBC	Perceived Behavioural Control
PDF	Probability Density Function
PID	Proportional Integral Derivative
PPA	Power Purchase Agreement
PV	Photovoltaic (Solar)
PyEMLab	Python based Electricity Market Lab
PyEMLab-Agg	Python based Electricity Market Lab - Aggregator
RCT	Rational Choice Theory
RDMS	Relational Database Management System
RL	Reinforcement Learning
RNN	Recurrent Neural Net
ROE	Return on Equity
ROI	Return on Investment
RPD	Recognition Primed Decision
RT	Real Time
RX	Receive.
SAJas	Simple API for JADE-based Simulations
SD	Standard Deviation σ or System Dynamics
SME	Small and Medium Sized Enterprise
SNA	Social Network Analysis

TD	Temporal Difference
TPB	Theory of Planned Behaviour
TSO	Transmission system operator
UK	United Kingdom
USA	United States of America
VaR	Value at Risk
VBA	Visual Basic for Applications
VRE	Variant Roth Erev
Wacoc	Weighted average cost of capital
ZIP	Zero Intelligence -Plus

Nomenclature

Bid_{Vol}	Bid Price Volatility
c	Constant
C	Intercept of linear relationship between numbers of customers and margin/fixed price
CDF_i	Cumulative distribution function of the clearing price and represents the probability that the bid price will clear.
CF_j	Cashflow in j^{th} year
COS	Cost of Sales – Payments paid to customers for bidding
CP	Clearing Price
CP_{Vol}	Clearing Price Volatility
CPX	Initial investment in year 0 – assuming constant real CPX
$D^{total}(t)$	Disposition Score at time t (Agent_Zero)
$Depr$	Yearly depreciation
E(r)	Expected return
F	Frequency
H	Hurst coefficient
m	Slope of relationship between number of customers and margin/fixed price
$margin$	Aggregators margin %
$NetIncome$	Profit after tax calculated as $(Revenues - COS - OPX - Depr) * (1 - tax\_rate)$
n	Number of bid buckets
N	Number of customers
N_{dom}	Number of Domestic customers
N_{Ind}	Number of Industrial customers (SME's)
$NumberofCars$	Average number of EV's per household
OPX	Annual Operating costs

p	Spectral Power
$P10$	10th percentile
$P50$	50th percentile
$P90$	90th percentile
P_{bid}	Average expected bid price
P_{clear}	Expected clearing price in market £/MWh
$P_{fixedprice}$	Fixed price offered £/MWh
$P_i\ (t)$	Logical score for the i^{th} agent at time t
$PenetrationEV$	Penetration of EV cars in market 0 -100%
$\Pr ice_i$	Bid price of the i^{th} bucket. In the algorithm used in the simulation $\Pr ice_i$ is the weighted average price of all bids in the bucket.
$Profit\ margin$	Profit expressed as % of Revenues calculated as $\frac{NetIncome}{\mathrm{Re}venues}$
r	Discount rate
R_f	Risk free rate or treasury rate
R_m	Average market return rate
$\mathrm{Re}venues$	Aggregator Revenues
$Revs_i$	Revenue for the i^{th} hour
$RevYr$	Revenues over year
ROE	Return on Equity
$S_i(t)$	Social score of the i^{th} agent – based on other agents connected to this agent at time t
$taxrate$	Corporate tax rate %
$V_i(t)$	Emotive (or Affective) score of i^{th} agent at time t
Vol_{mwh}	Average volume of customers (MWh)
$VolumeMwh_i$	Volume in i^{th} bucket
w_{ij}	Weight between i^{th} and j^{th} agent
WC	Working Capital
α	Scaling exponent
β	Beta for company or stock/share

Δ	Delta – Option Greek
λ	Arrows Risk Aversion Coefficient
ν	Vega – Option Greek
σ	Standard Deviation or Volatility
σ^2	Variance of Returns
$\pi_{percent}$	Profit margin – Net Income/Revenues
γ	Gamma – Option Greek

Acknowledgements

I wish to thank my supervisors, Dr. Ivana Kockar and Professor Stephen MacArthur, for their guidance and scholarship throughout this period and for permitting me the freedom to pursue my own research interests. Most of all, I wish to thank my wife Fiona, and my two daughters for their support throughout my PhD.

This thesis leverages several open source software libraries developed by researchers from other institutions written in Java, Python and Netlogo [1]. I would also like to thank the researchers from TU Delft in the Netherlands for sharing their ABM framework EMLab [2-5] and providing me with some new additional modelling techniques. I am similarly grateful for the work by Joshua Epstein (Sante Fe Institute, New York University) for his work on the Agent_Zero framework which I have extended to provide customer agents with "emotional intelligence" in a power setting. The thesis also draws heavily from my work on the SmartNet project [6] where my initial ideas for developing aggregator simulation agents was formed.

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Chapter 1

Introduction

This thesis examines the interaction of commercial power aggregator companies with customers in a distribution network setting. Learning algorithms and other heuristics are used to mimic behaviours of the following key actors (generators, aggregators and customers) in the power network domain[1]. In this chapter the motivation for research into commercial power aggregation is explained, the problem and the key research questions under consideration are defined and the principle research contributions are stated.

1.1 Research Motivation

A need for flexibility on the distribution networks is caused by the addition of Distributed Generators (DGs), and that causes a need for customers to provide flexibility and manage their demand. Traditionally, customers used the electricity when they needed it, but they are now managing their demand due to external forces associated with economics and the environment. The addition of large numbers of electric vehicles (EV's) into the distribution system will make predicting demand more difficult. EV's are stochastic and mobile, whereas demand profiles were historically

[1] Note other key actors like DSO's (Distribution system Operator), DNO's (Distribution Network Operator), TSO (Transmission System Operator) and ESO/ISO (Electricity Supply Operator/Independent System Operator) are modelled but have not be given any learning behaviours in this work.

fixed in location and reasonably easy to predict.

In the context of these Distributed Energy Resources (DERs)[2], certain regions (UK, US, Europe and Australia)[3] are making progress towards allowing consumers to interact more fully with the grid so to provide much needed flexibility because of the addition of stochastic resources like renewables and EV's. This, however, will present challenges to existing power system agents/actors like system operators such as TSO's /DSO's, as the potential number and complexity of the interactions with millions of smaller participants could overwhelm them. In addition, in order to ensure competition, markets for provision of these services need to be established and managed. Thus, there is a need for specialist third parties to manage these interactions, which are typically referred to as aggregators, and whose role is to help relatively smaller participants engage with the market. These smaller participants will be providing much needed flexibility to help operate such low carbon power systems. As aggregators are also businesses looking to provide services, they need to find appropriate business models that will satisfy their stakeholders. Future distribution flexibility systems will therefore require the participation of new actors like domestic customers and aggregators. The behaviour of these actors will impact on Distribution Operator's operations, their longer term planning and will impact on Regulator's market designs. Unfortunately, current tools do not adequately represent human or

[2] Small units connected to the distribution grid with possible two-way flow of electrical power. Common examples of DERs are Distributed Generators (solar, wind), battery storage, electric vehicles (EV) and active demand response (load that can change its consumption to provide flexibility to the system).

[3] Note the Thesis will focus on UK flexibility markets but the work presented will be applicable to other regions around the world.

aggregator behaviour in their models. This is an important for a number of stakeholders including regulators, customers, aggregators and the DSO's. In particular, the Distribution Operator will need to better understand the behaviour of customers and aggregators providing flexibility to their system in the short term, but will also need to account for these behaviours for their long term planning. A tool implementing human behaviour is therefore essential if appropriate designs are to be formulated, in a market with millions of participant's e.g. Domestic customers. The aim of this thesis is to develop a model/framework that will help planners and analysts better understand how these different business models/market designs will fare under different conditions, and how they affect consumers and the power system at large. Due to its ability to model behavior and interactions, Agent Based Modelling (ABM) provides an appropriate methodology to investigate various questions about these actor interactions.

A significant body of work has explored aggregation from an algorithmic and optimization point of view [3-6], but there is a lack of work looking at aggregation of customers in general, as well as the detailed interplay between multiple aggregators and consumers with social interaction[4]. In addition, there is little work in investigating economic modelling, decision-making processes and their impact on the aggregators themselves, as opposed to those focused on optimizing participation of particular technologies.

Current aggregation business models [7-9] in the sector are relatively

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[4] Much of the work has focussed on optimization in EV aggregation.

straightforward, typically using a margin based fee model[5], however. it is reasonable to expect that business models will inevitably evolve over time. To evaluate that change, it will be important to consider the following key issues:

- How will business models evolve and what business models are likely to prosper and under what conditions? Note the thesis will focus on a market that assumes consumers are bidding flexibility services in real time, one hour ahead. It is assumed that consumers will install the appropriate hardware so that flexibility can be provided via automation. Aggregators would provide the appropriate signals and measure flexibility deliveries. Note the thesis assumes costs for these automation devices and represents them in abstract terms in the simulation. Alternative models currently being instigated by the Distribution Network Operators (DNO's) involve paying a fixed ("availability charge) and variable utilization charge (£/MWh). They provide signals and instructions to the flexibility providers, via an automated process using dedicated communication lines and the use of Application Programming Interfaces (API's). This particular business model is not addressed in the thesis.
- How will customers react to aggregator offers? What percentage of customers will take up these offers?
- Is aggregation good for consumers? What is the scale of these benefits?
- How will aggregation affect electricity market prices?

[5] Customer gets paid £x/MWh – aggregator takes 30% of this value as a fee.

- How will system operators interact with aggregators and what will be the impact on system operation?

This thesis addresses the first four issues mentioned above, while investigation of the last issue can be found in [6-9].

1.2 Problem Statement

The provision of Demand Side Response (DSR) and flexibility in a future low carbon distribution system will be necessary if the power industry is to reduce costs. Market based DSR and flexibility mechanisms delivered via aggregators are estimated to provide a benefit of £2.4 – 9.7 Billion per year (2023 real terms) by 2050 [10-13][6]. Individuals and companies participating in a future electricity balancing or flexibility market must utilize tailored business models and understand how markets react if they are to be profitable. Furthermore, actions of such actors will affect others and may have adverse effects on the power grid itself and there will be a need for co-ordination between aggregators and network operators to avoid these problems. Although it is early in the process, full deployment of a flexibility system involving many new stakeholders will require new tools to be developed to understand these various effects. Currently there is no holistic modelling approach or tool that captures the behaviours of these new actors in an existing power setting.

In addition, "Energy is consumed in social environments and in the presence of social peers. But social interactions do not just happen alongside energy behaviour —

[6] Flexibility services will reduce the need for infrastructure reinforcement. Note costs have been escalated form 2015 to 2023 real terms.

the two are intrinsically linked." [14]. Social science researchers have started to develop conceptual frameworks to capture these social dynamics [15-17], but no computational model incorporating emotions and social interaction in the aggregator domain exists at present. Creating a framework which can include power networks, customers and their social relations with themselves and aggregator companies (and others), would be an important first step in providing a more holistic model of low carbon power networks. Without this aspect, policies would fail to take account of the impact of social interactions and customer psychology on system operation.

Traditional modelling of markets using Computable Generalized Equilibrium (CGE) models like Times Markel [18] are simplified, and miss modelling of some aspects of system operation. They also do not sufficiently capture the evolving behaviour of participants like aggregators and customers. A review of energy modelling approaches shows that there is major focus on techno economic systems (e.g. Times Markel) rather social systems [1]. Agent Based Modelling (ABM) makes up less than 1.5% of all the models used in the domain (Table 1 from [1]). Agent Based Modelling provides an approach that will capture these types of behaviours, but no frameworks or methodologies currently exist that provides a simulation of customers interacting on social networks with aggregators that are modelled as commercial enterprises. This is discussed more fully in Chapter 3 where literature is reviewed and the case is made for the development of a more complex model.

The aim of this thesis is to present a novel framework of aggregator, generator, ISO and customer interactions using an ABM methodology and use it to explore the following key research questions.

1.3 Key Research Questions

The following are the key research questions addressed in the thesis:

- How can we model aggregators to make them more representative of what a commercial aggregator company would do? What components do we need to model and how should we model them, e.g. how to include risk management and business model representations?
- How can we best represent future consumers that provide flexibility? How will these customers interact with aggregators?
- How do we capture the softer aspects of consumer responses such as interactions on social media or other psychological impacts such as emotions?
- How can we combine all these aspects to model a market with around 50,000 domestic customers – the size of a small city such as Dundee or York in the UK[7]?
- How will these actors interact under different market and network conditions? What will be the impact on market clearing prices and how will they evolve? Can patterns be extracted from these simulations that would be helpful to various stakeholders?

1.4 Overview of Modelling Approach

The aggregators in this thesis compete with other suppliers, such as competing aggregators, generators or large industrial consumers, in the markets for wholesale

[7] Assuming three people within each household. That is population size ~ 150,000.

power balancing and auxiliary services. Figure 1-1 shows the main concept of the model developed in thesis.

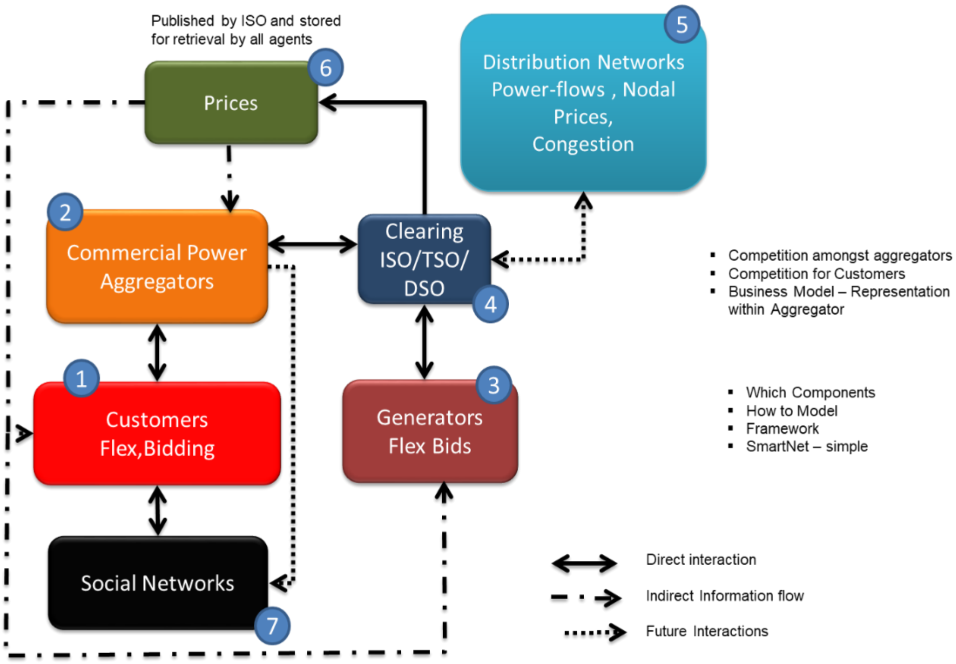

Figure 1-1: Actor interactions in proposed ABM framework

Note that in practice block⑤ would be included within block ④, but is shown separately as this will be the subject of future work. Commercial power aggregators②[8] interact with their domestic and industrial customers ① by managing flexibility bids[9] sent from these various entities. These bids, along with those from generators③, are submitted to the market operator (e.g. ISO/DSO/TSO④) who clears the proposed flexibility market using economic dispatch[10]. In future work, an AC OPF

[8] See numbering on Figure 1-1.

[9] Note large industrial customers might bid directly to the TSO/ISO and commercial entities connected at the Distribution level could bid directly to the DSO.

[10] It is not currently clear who will operate this market, e.g. will it be an ISO, a DSO or a combination of TSO/DSO organizations.

representation of a distribution network will provide these prices at various nodes and impact on the ability of some bids from customers to be dispatched⑤. Cleared prices ⑥ are published for use by various participants and are also used to adjust bids. Customers can chose between a number of aggregators who compete with each other for flexibility and acquiring customers. Domestic customers currently may gossip over a social network⑦[11] by sharing contract price information and details on the performance of their current aggregators. The dotted line between ② and ⑦ (future work) represents the ability of aggregators to influence social media using their own social media accounts or via bulk advertising channels.

In the proposed framework, consumers and aggregators are represented as learning agents using a trading heuristic[12] based on Dave Cliff's Zip trading agent [19-21] to determine the best course of action to achieve their goals[13]. For example, aggregators can take bids from consumers and manage these bids when participating in the wholesale/balancing market. On the other hand, aggregators need to entice customers to participate in their services, while also having to take into consideration customers' welfare. Aggregators can offer different contract terms to entice additional customers. Moreover, social customer interactions may play an important role in customer behavior. Customers can interact with other customers and, in this model, a novel approach based on the Epstein's Agent_Zero framework [10] is utilized.

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[11] Note specific contract conditions may inhibit the sharing of this data.

[12] Alternative representations could make use of reinforcement learning or other learning paradigms.

[13] Generators bid at marginal costs in the majority of the simulations used in this work. Note a sensitivity case uses the ZIP trading learning paradigm to update generator bids.

1.5 Research Contributions

The research presented in this thesis pertains to the academic fields of electrical power engineering, business, economics, risk management and Agent Based Modelling (ABM). The principle contributions made by this thesis are:

1. The first application of an extensible Python based ABM framework that includes the interactions between: (i) customers using an "agent_zero" based framework tied to a social gossiping network; (ii) competing aggregators with business models (including risk management) in the context of a future wholesale flexibility/balancing power market. The framework is based on the Java based EMLab [2, 3, 22], agent simulation software engine. In order to simulate short-term (hourly) interactions between participants, new agents have been created, and code written. PyEMLab[14], as far as we know, is the first structured power focused ABM simulator built solely in Python and provides a framework for future adaption for power domain modelling. Importantly it opens up ABM to Python modelers in the power domain with a clear structure and a scripting language/methodology in Python. "PyEMLab–Aggregator"[15] is the aggregator specific version of the more generic PyEMLab simulation framework used in this thesis.
2. Development of a real option approach using an exotic three-asset Monte-Carlo based option to represent risk in a power aggregation market. The aggregator

[14] PyEMLab is the Python port of EMLab developed by the thesis author.

[15] Shortened to PyEMLab-Agg.

agent incorporates a risk model to replicate the corporate risk management process.

3. Development of aggregator business models, not currently addressed in the literature. This includes a detailed cost model of aggregator operating and capital expenses and a static view of aggregator economics.
4. Extension of the Agent_Zero framework to model emotions, economics and social impacts. When social networks are combined with the Agent Zero framework, social interactions that influence the aggregator choice can be seen
5. Use of an ABM framework to investigate the interactions of these agents under a number of different parameters – and the identification of key drivers.
6. Development of a visualization model using linear approximations that could prove useful to stakeholders like regulators. The model will allow stakeholders to experiment with key parameters to help understand their impact on key performance measures.
7. Innovative use of Fuzzy Cognitive mapping (FCM) in an Agent Based Modelling setting, to aid in the validation and understanding of the dynamics of complex systems such as those modelled in this thesis.

The publications that have resulted from this thesis are:

- Howorth, G & Kockar, I 2018, Do we need a new architecture for simulating power systems? A position paper. in *Proceedings of 8th International Conference on Simulation and Modeling Methodologies, Technologies and*

Applications. vol. 1, Portugal, pp. 190-197, Simultech 2018, Porto, Portugal, 29/07/18. https://doi.org/10.5220/0006917801900197

- Howorth, G & Kockar, I 2019, 'Simulating a commercial power aggregator at scale: design and lessons learned' Simultech 2019 9th International conference on simulation and Modelling, Prague, Czech Republic, 29/07/19 - 31/07/19, .

- Vigano, G, Rossi, M, Sels, P, Leclercq, G, Gueuning, T, Pavesi, M, Vardanyan, Y, Ebrahimy, R, Jimeno, J, Ruiz, N, Howorth, G, Camargo, J, Hermans, C, Spiessens, F & Svendsen, H 2019, SmartNet simulation platform. [Glasgow].

- Rossi, M, Viganò, G, Migliavacca, G, Svendsen, H, Leclercq, G, Sels, P, Pavasi, M, Gueuning, T, Jimeno, J, Ruiz, N, Camargo, J, Hermans, C, Spiessens, F, Vardanyan, Y, Ebrahimi, R & Howorth, G 2019, 'Testing TSO-DSO interaction schemes for the participation of distribution energy resources in the balancing market: the SmartNet simulator' Paper presented at The 25th International Conference and Exhibition on Electricity Distribution, Madrid, Spain, 3/06/19 - 6/06/19, .

Applications of this Work and Resulting Publications

The aggregator model framework developed during this thesis has been adapted for use on a demonstrator project based in Scotland for controlling assets using a virtual power plant solution. Rather than simulating assets, the adapted version of the software uses real time schedulers to read asset data, forecast output and control assets in real time. Papers associated with this work are listed below.

Application - Published Papers

- Howorth, G, Kockar, I, Tuohy, P & Bingham, J 2022, 'An enhanced virtual power plant for flexibility services into a local area (including EV's),' in CIRED Porto Workshop 2022: E-mobility and power distribution systems, 2022, vol. 2022, pp. 970-974.

- Howorth, G, Kockar, I, Tuohy, P, Flett, G & Bingham, J 2023, 'Enhanced Virtual Power Plant Design and Implementation Lessons', The 27th International Conference and Exhibition on Electricity Distribution, Rome, Italy, 12/06/23 - 15/06/23.
- Howorth, G, Kockar, I, Tuohy, P, Flett, G & Bingham, J 2023, 'Business Models for Virtual Power Plants and their Impact on Economic Operation' The 27th International Conference and Exhibition on Electricity Distribution, Rome, Italy, 12/06/23 - 15/06/23.
- Howorth, G, Kockar, I, Tuohy, P, Flett, G & Bingham, J, 'The Impact of Forecasting Accuracy on the Economic Performance of Flexibility Provision', The 27th International Conference and Exhibition on Electricity Distribution, Rome, Italy, 12/06/23 - 15/06/23.

This thesis also resulted in a participation in an ETP PECRE visit to TU Delft over a period of 2-3 months to work on developing ABM frameworks for simulating power networks using the EMLab framework [23].

Work on the coding and development of the Curtailable Generation Curtailable Load (CGCL) aggregator by the author in the SmartNet project [9] was also completed during the thesis and forms the basis of the aggregator bucketing system described in section 7.2.1.

Moreover, the thesis relies on the experience and work associated with the author's prior industrial experience and development of techno-economic analyses on a variety of subjects including power generation, new technology assessments, corporate investment modelling and accounting.[16]

1.6 Limitations/Exclusions

The focus of this thesis is on future flexibility markets[17] in a low carbon distribution electricity network. The interactions between the market aggregators and customers and the power network is considered in the context of Agent Based Modelling framework that implements a simple model of agent psychology using the Agent_Zero framework although other frameworks and computational solutions could be used. The model has been developed in Python and uses the EMLab[18] architecture as its agent base. Economic dispatch has been used to clear the proposed flexibility market,

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[16] See https://scholar.google.co.uk/citations?user=NjAG_QsAAAAJ&hl=en for examples.

[17] The thesis assumes that the "flexibility" market is used to clear bids from aggregators and other entities like generators. Consumers are assumed to bid in their flexibility to aggregator companies who package such bids into small bid bundles. Balancing mechanisms are usually associated with transmission balancing, whereas flexibility is associated with "balancing" services at the distribution level.

[18] EMLab (TU Delft) is an electricity based ABM written in Java but the author ported this model to Python (PyEMLab) during an exchange visit with Delft University in 2019.

primarily so that an understandable proof of concept can be developed before moving on to including more realistic networks using an AC OPF methodology.

Modelling of Electric Vehicles (EV's) and customer flexibility has been simplified in that temporal shifting of power and locational issues associated with delivery have been ignored. However, a more sophisticated representation of customer and aggregator bidding has been presented.[19] Python has been used as a basis for this development particularly for its development speed, as opposed to its run time speed.[20] An important line for future work would be to extend the model to accommodate future elements such as a more detailed EV model, better congestion modelling and the inclusion of longer-term investments and other new technologies and innovations.

Time constraints have necessitated that this work focus on a few scenarios, but additional assumptions and other network structures could be investigated in the future. Other simplifications have been made including:

- A limited number of business models have been simulated (six).
- Synthetic customer data has been used - uniform types of different customers that may not reflect the true demographics of the region of interest. Use of commercial consumer databases such as Experian's Mosaik segmentation database [25-27], could provide a more accurate view. Additionally, judicious use of surveys to help synthesise such data could be used, but this is beyond the scope of this work.

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[19] Based on the SmartNet model representations.

[20] Java in theory provides a significant run time advantage whereas Python is much easy to develop in reducing development times by a factor of 5 [24]. However, with use of Python Numpy (C based), the speed advantage is much reduced.

- A social network based on a Facebook and Twitter structure has been used. Customers have been randomly assigned to the network so an affluent customer could be placed near to many less affluent customers. This may be an unrealistic assumption.
- Apart from conventional generation providing competing flexibility no other commercial entities other than aggregators are simulated. Companies providing alternative business models like Peer to Peer Trading (P2P) have been ignored but the framework can be extended to include them.
- Aggregators could spend to influence consumer-buying decisions using advertising. Aggregators could also participate in social media and provide "fake news". Although these aspects could be added later, these have been ignored for now.
- In these simulations, only domestic customers and aggregators can currently change their bids in any sophisticated manner. Industrial customers and generators bid at marginal costs provided to them in the initialization of the simulation.
- Entry and exit of customers and aggregator companies into the simulated market have been ignored in this first phase of the simulations.
- The impact of TSO/DSO interaction and coordination schemes on the market are not simulated in this work.[21]

[21] This was one of the purposes of the SmartNet project.

1.7 Thesis's Implications

This work provides important implications to aggregators, customers (industrial and residential), systems operators (DNO's and TSO's), regulators and Government. Finally, there is an impact on all of us, as taxpayers[22]. The framework presented can be extended into other ABM frameworks such as EMLab[2, 3, 22], which focusses on longer term investment decisions, or linked to other open source Python based software such as PowerGAMA [28, 29], PyPower [30], Ding0 [31] to simulate power flows and transmission or distribution upgrades.

1.8 Thesis Outline

This thesis is organized into nine chapters as summarized in Figure 1-2. Chapter 2 provides background information on the UK balancing market in the context of this thesis, and introduces aggregation as a concept (including aggregators). Note balancing markets currently operate at the transmission level but is used as a surrogate for the operation of a future flexibility market at the distribution level.

Chapter 3, provides a review of the current state of the art with regard to ABM power modelling, particularly in the context of modelling aggregators in a low carbon power network. It discusses a need for power ABM simulators as only few currently exist [32] with none adequately taking into account of how customer psychology or emotions influences their decisions.

In Chapter 4, business model frameworks[23] and definitions are introduced and

[22] Reductions in investment could save trillions of £ in future grid investments, some of which will be subsidised by Taxpayers.

[23] Including an Industry Analysis of similar businesses – Appendix A3.

publications on power based aggregation models are reviewed, but, as the chapter illustrates, literature focuses on current business models and provides little detailed data on the economics and costs of such models. The chapter concludes on these gaps by developing a business model framework for future aggregators, and provides a cost model for an aggregator business. This multi-dimensional business model has been developed from business model frameworks introduced in the chapter. Six business models based on two dimensions of that model (Revenue generation model (3) vs Risk Management stances (2)) are developed and used in analysis later in the thesis.

Chapter 5 describes risk management as a process and uses real options to value the portfolio of an aggregator and its risks. Real options valuations of energy retailers and power contracts in literature are reviewed, and the chapter illustrates that current literature does not address the valuation of aggregator contracts, although such real option techniques are useful in understanding and valuing risk in an aggregator context. The chapter describes a put option framework to value and mitigate risk and presents theoretical results under a number of assumptions.

Chapter 6 introduces the frameworks to be used for modelling customers and includes social network modelling. A review of different models used in the Social Sciences to represent emotions and psychological influences are discussed. The Agent_Zero model is selected as a tractable and realistic but "simplistic" model to represent emotional and cognitive elements. There is currently no literature in the ABM power domain that uses such an approach. It provides human like responses without the complex modelling exhibited in the other models discussed. Future versions of the model framework may use these other methods. Chapter 7 details the

ABM framework and highlights design choices and assumptions. Chapter 8 presents an ABM case study based on a UK city the size of Dundee or York with 50,000 domestic customers and 4500 small to medium sized industrial customers. The output is analyzed, and trends and simulation-related drivers are noted. Validation and verification of the model output is also discussed in this section.

The primary conclusions drawn from the results in this thesis are summarized and discussed in Chapter 9. The PyEMLab-Aggregator[24] software provides a rich environment in which to explore various assumptions and different parameter values. Various long and short-term dynamic patterns are seen and it appears that 4-5 aggregators will be required in a region to provide the maximum benefits to consumers. Shortcomings of the approach are noted and the broader implications are addressed. Some ideas for further work are also outlined in this chapter as well as throughout the text, including concepts related to extending this framework.

[24] Known as PyEMLab-Agg.

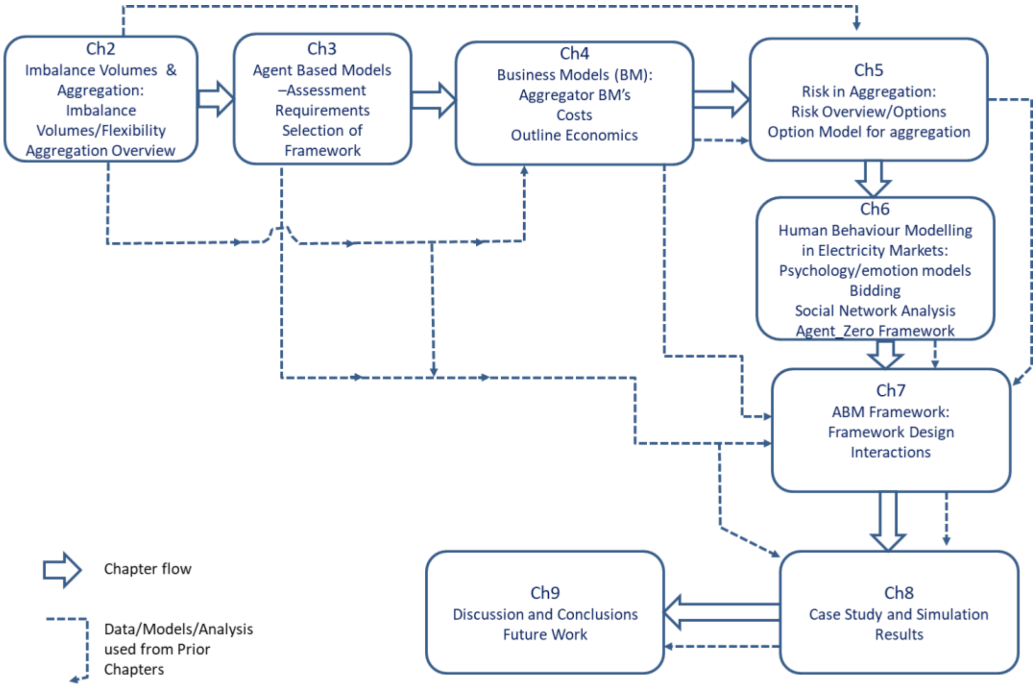


Figure 1-2: Thesis structure overview

Chapter 2

Imbalances, Flexibility and Aggregation in Low-Carbon Power Systems

2.1 Introduction

Markets for flexibility services are currently evolving. Current markets are focused on transmission balancing volumes but distribution level markets are becoming more prevalent, but there is a lack of data for these markets. The balancing market provides useful data and lessons for the development of the future flexibility markets at the distribution level, so has been used as a surrogate for a future distribution market in the simulations used in this thesis. Note that flexibility is a term usually associated with distribution level markets, whereas balancing is associated with transmission level assets.

Imbalance volumes resulting from forecast errors and system outages drives the need for flexibility[25] and is an important input into any simulation looking at flexibility markets. An understanding of how this demand for flexibility varies through time and with different drivers is important in the context of this thesis. This chapter starts with a brief introduction to the UK national electricity supply in the context of future volumes under different scenarios. It is given along with background information on

[25] Volumes for balancing services arises from the difference between real time generation/consumption and forecasts provided the prior day.

the current electricity Balancing Mechanism in the UK and the drivers of imbalance volumes in a future market. A review and analysis of historical UK hourly demand and balancing data is also provided and used in compiling a data set for simulation in later chapters. Secondly, an introduction to the concept of aggregation is made, along with an outline model of how one might model such aggregators in a computer simulation in a flexibility market using such aggregators. The structure of chapter is shown graphically in Figure 2-1.

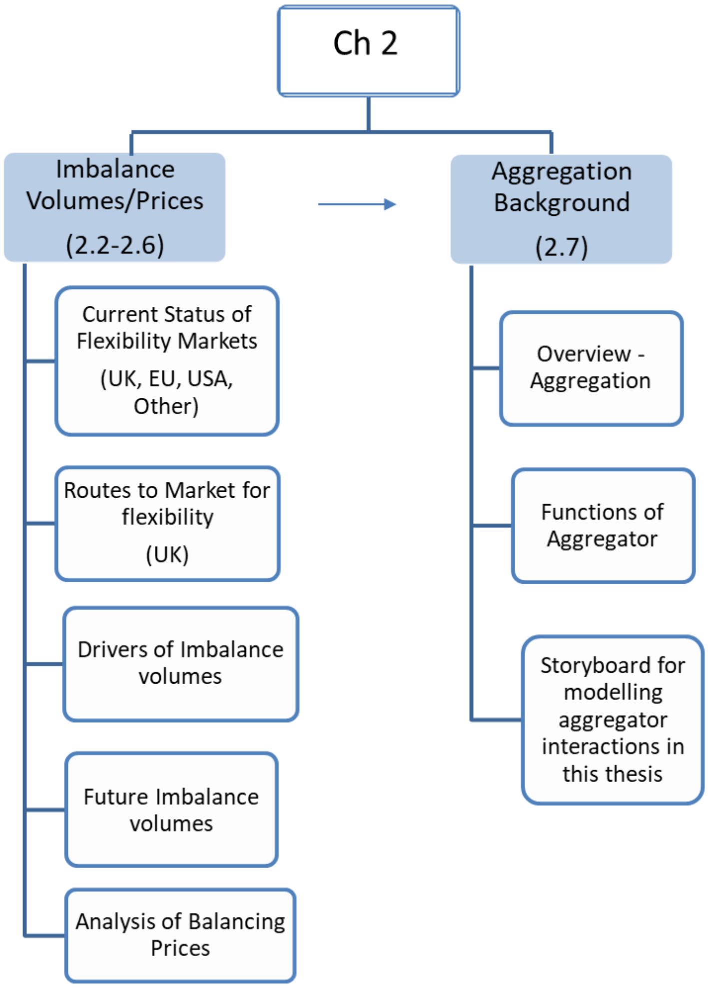


Figure 2-1: Overview of Chapter 2

2.2 Current Status of Flexibility Markets.

The UK is considered a leading innovator in energy flexibility markets [33] and as such this thesis focuses on these markets. It should be noted that the flexibility product analysed here is a general category of power stability products, some of which are mentioned in section 2.3. As one of the first regions to evolve its energy mix with a higher penetration of renewable energy, the UK has had to develop through an evolutionary process, various markets both long and short term to meet the needs of DNO's, National Grid ESO (TSO) and its customers. The EU has followed a similar process but has lagged behind in its wider implementation of flexibility markets because of its slow implementation of EU legislation. Reviews of the current state of the art in flexibility platforms and flexibility markets in general can be found in [34-40]. Section 2.3 provides an overview of the various routes to market for flexibility providers in the UK and discusses the evolution of the UK markets and current state of play.

Both the UK and Europe are moving towards providing flexibility markets and there has been many initiatives and pilot studies performed on market flexibility systems e.g. GOPACS, NODES, PicloFlex, CoordiNet etc. [35]. The market setup is similar amongst EU countries, but each of them its own peculiarities. Note that most of the platforms providing flexibility are owned and operated by the TSO/DNO's or retailers like Centrica. Few are independent (e.g. Piclo [UK] and NODES [Norway]) [36]. The UK market currently purchases balancing services and flexibility on a pay as bid basis whereas Europe uses the pay as clear method.

Although the USA markets have provided flexibility products for the day-ahead and Intraday markets there are currently few examples (eg Piclo NewYork State [41]) of local flexibility markets at the distribution level, as studied in this thesis.

Piclo for example opened what is considered to be one of the first independent B2B platforms/Exchanges (Auctions) for flexibility services initially for longer term flexibility but this is slowly migrating to a real time flexibility platform. For example, National Grid ESO's Local constraints market (LCM)[26] launched on Piclo recently in the UK with day-ahead and intraday bidding at numerous power grid nodes (0.4 – 66 kV) [42] . Piclo is also rolling out its platform to other regions of the world [43], including Lithuania [44], Portugal [45], Ireland [46] and the USA [41]. It also completed its first Capacity market trade in March 2023 [47].

2.3 Routes to Market for Flexibility Services (UK)

The UK provides many routes to market for the sale and import of electricity and some specifically for flexibility or imbalance services. Flexibility providers do not have to sell specifically to flexibility markets they could for example, contract out all their output to a Power Purchase Agreement (PPA). The sale of services to the TSO (balancing services), DSO (flexibility services) or both are shown in Figure 2-2 below. It shows how the market has evolved over the last five years, from one that was essentially a long term market purchasing reserve[27] or short term operating reserve, to one that allows users to purchase these services on a day ahead basis. Note the TSO's/DNO's still purchase on a long term basis but are starting to purchase shorter

[26] Opened May/June 2023.

[27] The reserve is mainly made up of synchronised generators.

term supplies on a pay as bid basis. Note interested readers should refer to National Grids ESO's website (see for example [48, 49])[28].

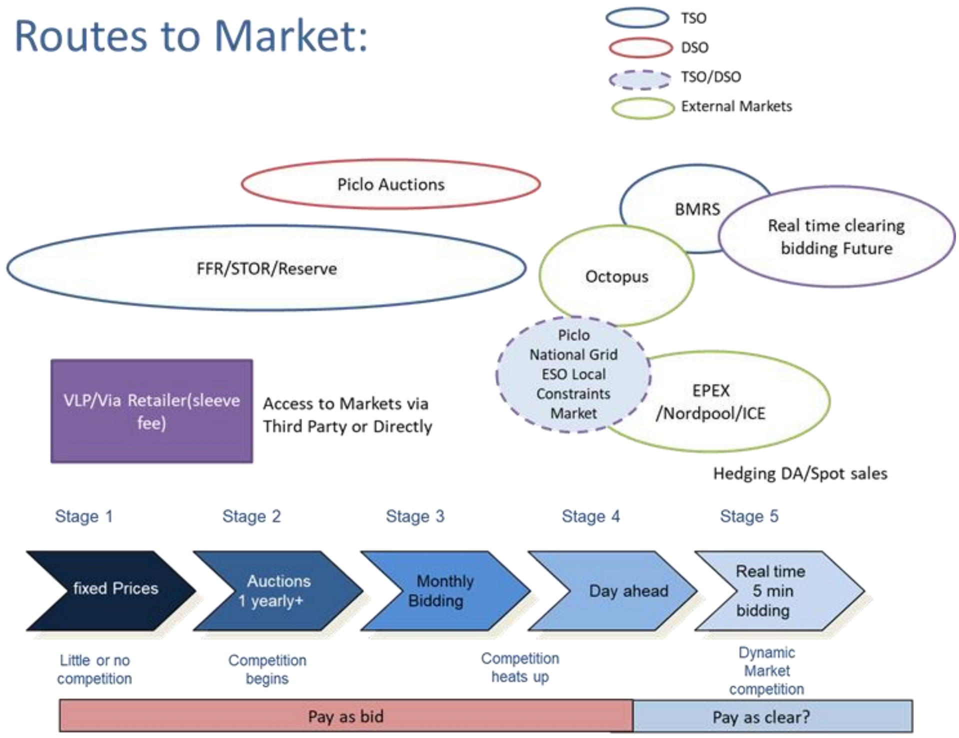


Figure 2-2: The evolution of balancing and flexibility markets

The currently envisaged markets for distribution flexibility and transmission services are summarised Table 2-1. The Piclo electronic marketplace for flexibility began in 2019 [50]. Elexon was established on 1 August 2000 to manage the Balancing and Settlement Code (BSC) ahead of the New Electricity Trading Arrangements (NETA) that went live on 27 March 2001 in England and Wales. Scotland followed in 2005. In the Elexon Balancing market place, "the auction gate opens 60 to 90 minutes before real time. During this window, market participants submit "bids" or

[28] Users can navigate to other services from this webpage.

"offers" into the BM". Real time bidding half hourly has therefore been around for a long time. There is one price for the whole of the UK and bids are made at the transmission level or Grid Supply Points (GSP). It should be noted that these flexibility markets are currently evolving. It is expected that future markets for flexibility would become more localized and potentially more volatile. One interesting development in the UK is the Piclo auction market for DNO flexibility. Auctions are carried out half yearly/yearly for flexibility at certain locations on the grid. Contracts can be provided for a number of months for a few hours per day or over a number of years e.g. five. Although data is becoming available for specific locations, data is still sparse[29].

Market	**Type**	**Comment**	**Reference**
Fixed Price PPA	Fixed Prices	Typically agreed contract price for sales and imports. Fixed price over year	
Octopus GO	Off Peak On Peak Pricing	Example of energy retailer offering on off peak price.	[51]
Octopus Agile	Dynamic Tariff e.g. based on Day ahead wholesale prices	Example of energy retailer offering dynamic prices linked to day ahead market	[52]
BMRS (Balancing Mechanism - Elexon)	Imbalance market price -UK wide. Transmission system Focussed - TSO	UK wide market. Minimum bid 1 MW. Transmission level service	[53, 54]

[29] Especially demand data at the hourly or half hourly granularity level.

Market	Type	Comment	Reference
Piclo/DNO	Flexibility Auctions for flexibility at the distribution level (400v – 33kV)	DNO/DSO Calls for agreed standby services at price set during one of Piclo's competitions. DNO specifies amount of flexibility required. Could be as low as 40 kW. Can supply long - term flexibility for a few hours per day for months or years. Recent developments include day and intraday bidding for NationalGrid's ESO LCM market	[42, 55]
Firm Frequency Response FFR	Short-term dispatch for reduction of power to stabilise overall system frequency. UK ISO provides dispatch signals to providers	Provision to wider UK grid. Transmission level service	[56]

Table 2-1: Summary of routes to market in UK

Aggregators would be able to mix and match flexibility services to these various markets[30], but this is not considered in this work as it focuses on distribution flexibility markets[31]. In practice, some of these markets would not be available to aggregators, as there are size and quality of connection limits placed on assets. For example, aggregated volumes must be at least one MW for the Balancing Mechanism (BMRS) market. The markets are still evolving. However, the Balancing Mechanism market does provide one of the few sources of real data on the price and volume movements of a potential flexibility market with bidding in real time and has therefore been used as a surrogate market for distribution flexibility markets in this work. In a recent development[32] Piclo has rolled out the Local Constraints Market (LCM) in Scotland, moving Piclo towards providing more real time bidding services. Although beyond the scope of this work Peer to Peer Trading platforms (P2P) present another route to market for providers of flexibility either through centralised (Piclo [58]) or decentralised platforms (Electron [59]).

2.4 Imbalance Volumes, Balancing Markets and their representation

2.4.1 Imbalance Volumes Overview

Currently volumes for balancing services (imbalance volumes [60]) arises from the difference between real time generation/consumption and forecasts provided in the prior day. Short-term changes in weather and outages of the power system (generation and demand related) result in these forecast errors. Flexibility is required to adjust

[30] Known as Value Stacking [57]. Not all services can be value stacked.

[31] Note because of a lack of data the transmission level Elexon's Balancing market (BMRS) is used as a surrogate market.

[32] May/June 2023. Piclo manage on behalf of NationalGrid ESO.

the volumes promised day ahead, so that the right amount of electricity is delivered to customers in real time.

Prices associated with flexibility/balancing services is in theory driven by the marginal cost of providing such flexibility and can be represented as a marginal cost (MC) stack.

The drivers of the historical market are summarized in Figure 2-3 (see [60] for a description of market operation).

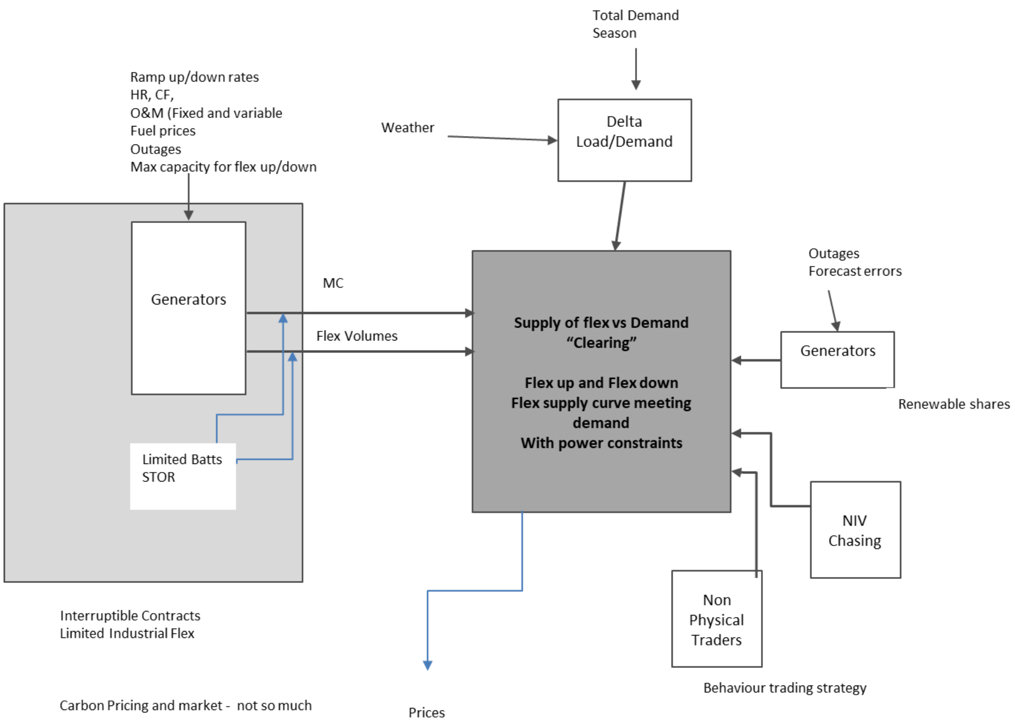


Figure 2-3: Current drivers of the UK balancing market

The left hand side of the figure is associated with drivers of price via generators marginal costs and balancing volumes (supply side). Marginal costs are driven by assumptions on capacity factor (CF) Heat rate (HR), fuel prices and so on. Generator balancing volumes by the capacity of the plant, and its ability to respond. In the current market some battery services and interruptible contracts can be used.

Forecast errors (generation and consumer demand) drive imbalance volumes and can be thought of as demand for balancing services (right hand side of the figure). In a theoretical market, assuming no constraints, price is determined at the point where supply meets demand. Imbalance volumes are expected to grow over time (see datasheet FL.03 [61]) by approximately 240 - 370% by 2050.

This historical market is characterized by a small number of players, often larger corporations controlling larger generating sets. Note although marginal costs and net imbalance volumes would be expected to set price, that in the last few years participant behaviours from trading have increased imbalance volumes and prices (see Net Imbalance Volume [NIV] chasing description in [60]). Behaviours of the balancing market players is thus an important determinant of the pricing in this market.

Historically balancing services have been associated with transmission, as little generation or demand response at the distribution level had been seen. In the future, the addition of flexibility services from domestic consumers and the addition of new actors like aggregators, the use of residential batteries and behind the meter generation will change this market (see Figure 2-4). In addition, flexibility will be required at the distribution level to deal with these actors actions. This distribution flexibility is known as flexibility as opposed to balancing, but the two are obviously interlinked. This thesis will focus on flexibility services at the distribution level. Participant behaviour would be expected to become ever more important in this new market structure.

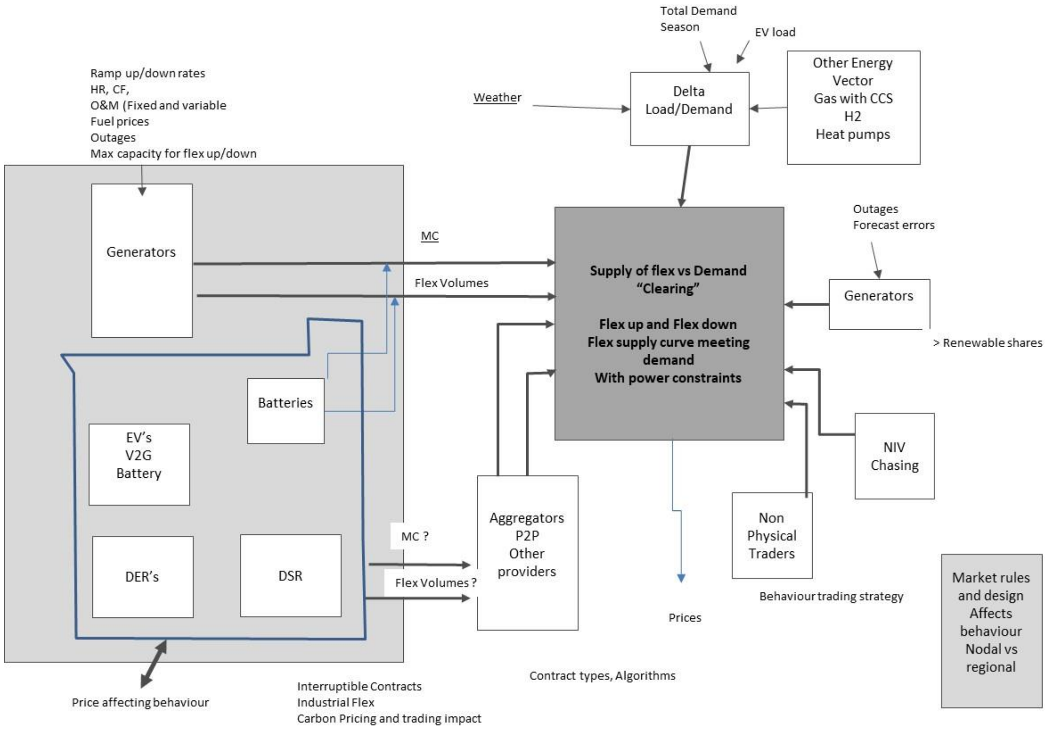


Figure 2-4: Future drivers of the UK balancing market

The use of imbalance volumes or flexibility services forms the heart of the work in this thesis and its associated simulation results, in that it drives the need for flexibility from domestic customers and others. The purpose of the following sections is to understand the characteristics of these potential volumes and associated prices in a UK context, so that it can be used in the case study/simulation presented in later chapters e.g. are the volumes random?; what do they look like?; and how should one represent it?

Unfortunately, the historical data on imbalance volumes and prices is that associated with transmission, and this thesis is focusing on distribution flexibility services where there is little if any data[33]. Ascertaining the impact of flexibility behaviour on balancing demand is an important but difficult question. There is currently no data on which to formulate models or views (note data with and without flexibility would allow us to formulate a model of how DSR has affected balancing demand patterns). Traditionally demand elasticity [62] has been used to model the impact of price on demand. Imbalance/flexibility volumes are likely to be a function of overall or total demand, the level of renewable penetration and the amount of flexibility supplied by new actors such as domestic consumers. The interactions between overall demand, price and imbalance volumes is likely to be more complex than that obtained from using elasticity of demand factors. In addition, elasticity factors are typically calculated over longer time-periods (e.g. a year), whereas flexibility is a real time concept. For now, there is no better an approach than using these elasticity factors, so this has been used in this thesis, to mimic price imbalance volume effects.

There is a wide body of literature on the elasticity of electricity demand with price and a number of papers review both short and long-term elasticities of electricity. In particular Labandeira et al. (2017) [63] surveyed 428 papers published between 1990 and 2016 and showed that the majority of the surveyed publications used various approaches, including different regions, and varied time frames, which led to significant differences in the estimations. The average short-run and long-run price elasticities of electricity demand were found to be -0.13

[33] Note some data is now becoming available on flexibility volumes associated with distribution networks Feb 2023.

and -0.37, respectively. Table 1 in this reference provides the ranges found in the various studies which range from [-0.9, -.07] for the short term and [-4.56, 0] - Long term. This research also found decreasing elasticities over time. Lijesen (2007) [64] provides a review of 23 papers for a number of regions and customer types. Table 1 in the reference provides a summary of these values for both long and short term. Long term elasticity values range from [-0.82 , -0.09] and short term from[-1.113,-0.04]. Table 2 in the same reference provides elasticity values associated with time of use pricing for five of the studies. Off peak elasticity pricing effects range from [-2.3,-0.003], where peak prices elasticity is [-1.25,-0.002]. Note Lijesen's own figures are even lower than those shown in his review. More recent studies for the EU (Csereklyei (2017)) [65] show that Electricity demand is highly price and income inelastic in the short run. The long-run price elasticity of industrial electricity use is between [-1.01, -0.75]; The long-run price elasticity of residential electricity use is between [-0.56,-0.53]. Elasticity over a year has been found to be around –0.3 in various studies [66] but this is case dependent e.g. country, on/off peak pricing, network structure. That is a 1% increase in price would decrease demand by 0.3%. Conventionally shorter terms effects are assumed to be zero but in Burke and Abayasekara's (2018) [67] US based study , a value between –minus 0.07 and minus 0.09 have been found (monthly basis). Note table 1 in Andruszkiewicz, Lorenc, Weychan's work (2019) [68] also provides a range of values for both short and long term and for different countries (Short term [-0.835,-.0014]; Long term [-1.652,-0.11]). Finally, Eliasson (2022) [69] examines hourly, daily, and weekly short run elasticity of household electricity demand in Sweden. Short run elasticities were found to be low Hourly - [-0.1,-0.0019]; Daily - [-0.09, -0.49]; Weekly – [-0.102,-0.19].

The modelling herein takes both effects and uses values of -0.3 and -0.08 respectively for long and short terms (monthly) elasticity, but it should be recognized that there are large differences in these values in the various studies. Future work should consider differences in these values.

In the next few sections, an analysis of historical balancing data for the whole of the UK is given. Public domain data does not provide granularity down to specific region.

2.5 UK Electricity Market Background: Future Scenarios of Total Demand

The UK's system operator, National Grid, forecasts that total demand for UK power will increase by 75% -120% by 2050, dependent upon scenario (Figure 2-5). [70][34]. It would be expected that the higher the demand the higher the requirement for balancing services.

[34] Note that later FES scenarios use different names for the scenarios, the results from the analysis are broadly similar.

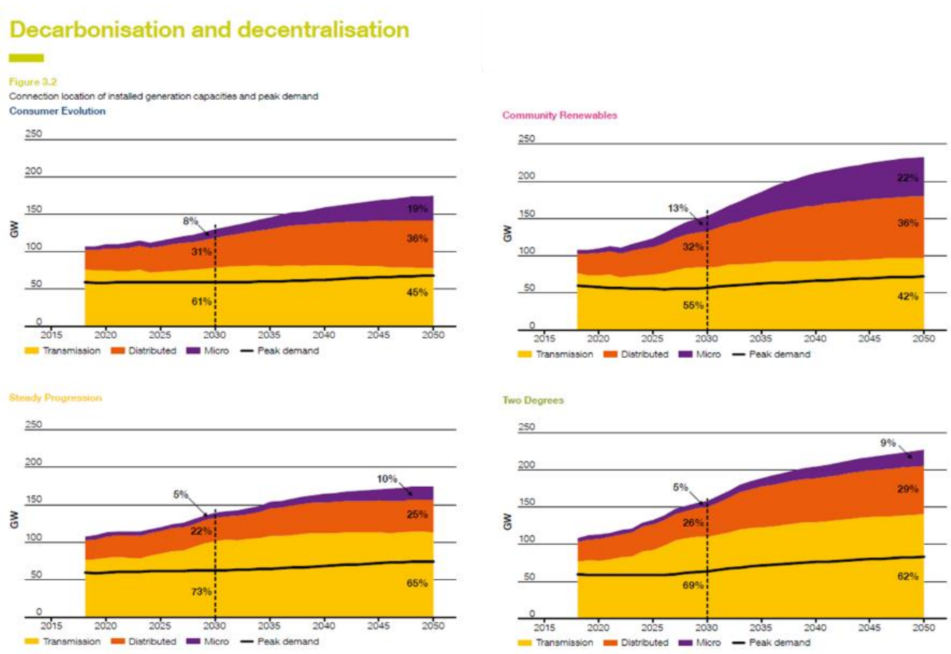


Figure 2-5: *National Grid Future Energy Scenarios (FES) 2019 [70]*

National Grid's "Two Degrees and Community Renewables" scenarios (2019)[35] meet the UK's 2050 carbon reduction target but features different levels of decentralisation in its assumptions. The "Steady Progression" and "Consumer Evolution" scenarios do not meet the 2050 target and all scenarios include a mix of technologies, but assume different levels of adoption. In all scenarios, demand for electricity grows. A greater decentralised focus will put more strain on localized systems i.e. at the distribution level (low to medium voltage).

Overall energy demand (gas and electricity) falls in the scenarios, but economic growth and the uptake in charging (35 million EV's in 2050) dwarfs any potential savings from efficiency gains in the other sectors. Interestingly, in a separate study

[35] National Grid publish these scenarios, annually.

[71], it is shown that younger generation lifestyle choice are eroding these gains in efficiency. It is unlikely that this effect is included in the future electricity scenarios.

National Grid recognize that “a smart flexible system will need new business models and services to match system needs with vehicle charging requirements and consumer preferences” [70] and that “the market will need to adapt to the changing plant mix. Key industry processes are likely to need reviewing, bringing with them opportunities for new services. Balancing[36], security of supply, affordability and efficiency in a decarbonized world presents new challenges”[72]. However, it is not clear what the new services will be, and what impact they will have on the system and how to best review them. This thesis provides a framework and methodology for helping with this review and provides additional insights.

In more recent years DNO’s in the UK have published their versions of the Future Energy Supply, DFES (see Scottish Power’s version of DFES [73, 74]). They provide slightly more granularity with yearly values at the Primary substation levels (33/11kV) and the Grid Supply Points (275-132kV). The output is broadly similar to the National Grid’s work and feeds into the FES work. Flexibility requirements are only shown at the yearly level from 2021 – 2050. Although good for yearly planning purposes, hourly data views required for simulating flexibility in this work are still absent. It does provide a view on the peak flexibility required (MW) at various distribution nodes and could be a useful source of data for future work.

[36] Note balancing in this context applies to transmission assets, but the comment equally applies to distribution flexibility.

2.6 Analysis of Balancing Prices and Imbalance Volumes

Using National Grid [75] and Elexon data [76] an analysis of balancing volumes vis a vis demand and wind penetration is shown in Figure 2-6 for the UK.

Balancing volumes vary through the year but are of the order of +- 15-20% of the expected day ahead volumes.

Figure 2-6 presents various graphs from an analysis of various balancing demand data sets over the period 2013-2015[37]. Although Figure 2-6 (a) appears to show slow downward trends of balancing prices with wind penetration levels, the historical relationship between price and wind penetration is still unclear. The influence of learning on balancing prices and increased competition is likely to have had an effect in these markets. In addition, wind penetration was at relatively low levels, during this period.

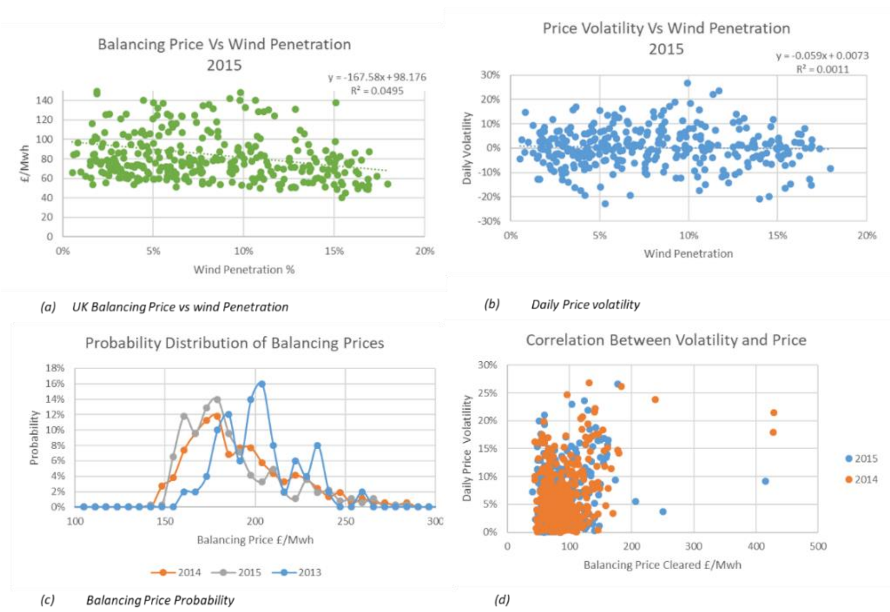


Figure 2-6: Analysis of historical UK balancing market data

[37] Later years, especially post Ukraine war start, show higher average values and greater volatility.

There appears no such trend in volatility of prices with wind penetration, although it is likely that other factors are at play here. In addition, aggregator/DSR levels would be low, so care should be taken in extrapolating any conclusions from this analysis. Figure 2-6(d) suggests that higher volatility is associated with higher prices, although this has large degree of scatter. Volatility time series trends (Figure 2-7), appear random with burst of activity, however it should be noted that this excludes any substantial effects from DSR or "flexibility at the distribution level in general.

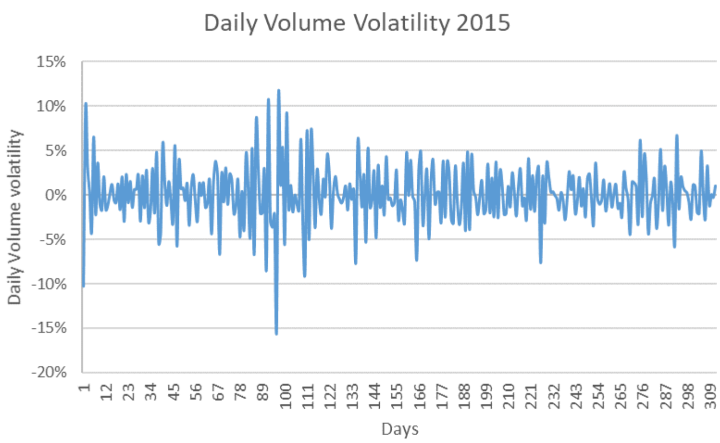


Figure 2-7: Daily balancing volume volatility 2015

Very different balancing volume patterns are found by year (see Figure 2-8). It is clear that it will be difficult to forecast these balancing patterns accurately as the patterns seen in Figure 2-8 will be dependent on outages, weather, renewable energy mix, and so on. So some sort of probabilistic forecasting model would be required to represent these patterns.

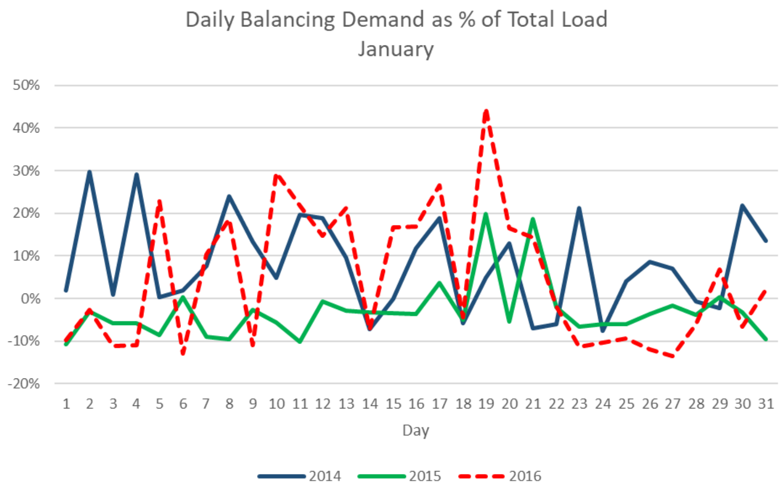


Figure 2-8: Daily balancing volume volatility for January

2.6.1 The Impact of Drivers on Future Imbalance Volumes and its Volatility

Simulation with real or simulated OPF network models under a variety of conditions would provide a useful methodology to answer the question of how will future imbalance or flexibility volumes will change. Unfortunately, this would involve a large amount of work and is outside the scope of this thesis and is left for future work.

The Future Energy Scenarios (FES) in 2022 [61] and the datasheet (FL.03) that accompanies it in particular, provides a view on how the need for flexibility will increase over the next 30 years. It shows that flexibility is forecast to increase by 61-153% by 2035 depending on scenario and by 244-370% in 2050. EV's and DSR are expected to provide 20-35% of that flexibility. Prior to this recent publication, there were few sources of how this flexibility would grow and its makeup. For the interested reader, Appendix O: O provides a bottom up analysis using forecast errors associated with weather, solar, wind etc. performed by the thesis author, to calculate how flexibility volumes would be expected to grow under different assumptions about renewables and EV penetration. It is shown that Balancing volumes expressed as a percentage of total demand could be as variable as 15-32% (peak), dependent on renewable energy mix and EV penetration levels. This analysis is based on UK wide data so specific area or other operational issues could increase these values.

Assuming a normal distribution,[38] this equates to a standard deviation (SD) of around 7% to 10%. This about twice as high as the volatility derived in the time series analysis presented in section 2.6 above.

This analysis therefore suggests that balancing volumes could be some 50% -100% higher in 2030, depending upon wind penetration and assuming a 30% EV penetration in 2030. Note a sensitivity factor that reflects this range has been used in the simulations presented in Chapter 8.

2.6.2 UK Domestic Flexibility Supply

Although demand is an important determinant of prices, flexibility supply from consumers, small businesses and generators will also form an important part of any system providing flexibility services. Flexibility from generators and Industrial customers can be assumed to be a few percent of the total supply[39]. The question is how much flexibility supply will domestic customers provide?

Drysdale Wu and Jenkins study [77] reviews and estimates domestic flexibility

[38] That ranges from +- 3 Standard Deviations.

[39] Based on historical supply from such actors.

potential for the years 2012 and 2030. Various figures in the reference show flexibility potential in summer and winter and by time of day for a variety of flexibility types including heating, cold and wet appliances, consumer electronics, lighting and cooking appliances. The study shows that about 28% of domestic demand could be used for flexibility services. Obviously not all of this would be used. For example Söder et al. [78] section 2.1.2 shows that after optimization, only about 75% of total flexibility capacity in Sweden is forecast to actually be used. In addition, particular households may not want to participate in a flexibility market. It is known from Ofgem figures, that current household demand without EV;s is around 11kwh/day, but EV penetration is currently very low.

Söder et al. [78] reviewed demand side flexibility capacity in Northern Europe and summarize capacities as a percentage of peak demand in their table 10 and the various tables contained within the paper. This is summarized in a different format in Table 2 below. Domestic market flexibility includes water and space heating, and other domestic flexibility sources.

Country	**Domestic Market Flexibility % of Peak Demand**	**All Markets % of Peak Demand**
Sweden	7.4 - 20.4	25.3 – 29.7
Denmark	5.4 – 9.6 (Table 3)	11.5 – 29.7
Norway	4.2 – 11.4	8.5 - 24.9
Finland	7.6 - 9.6	29.1 - 31.1
Estonia	3.6 – 14.7	15.0 - 26.1
Latvia	0	5.1 - 6.1
Lithuania	0	3.5 – 4.6
All countries in study	5.6 – 13.1	15.3 – 29.5

Table 2-2: Northern Europe flexibility capacity summary: Source - Söder et al. [78]

The various studies show that flexibility capacity will be market dependent but lie in the range 15-30%. The UK study in [77] suggests that total flexibility potential (without EV's) is around 28% for domestic customers. EV's will provide additional potential. This thesis will initially assume that only 14% i.e. 50% of the potential will be available for flexibility bidding and aggregation. Sensitivities to this quantity will be investigated. In addition, flexibility potentials will vary through the year (figures 19 -20 in [77]). These profiles have been normalized and an EV charging discharge profile has been added to the curves. Curves have also been extended to cover 8760 hours in one year. Customer input data for the simulations in Chapter 8 includes for many different types of flexibility, including EV potential, so a simple test[40] in the code allows the simulation model to select between two different normalized curves.

2.7 Aggregation: Overview and Modelling Construct

The objective of the EU Horizon 2020 SmartNet project [6] was to compare different coordination approaches between actors such as Transmission operators (TSO), Distribution System Operators (DSO) and customers. To facilitate interaction between, potentially, millions of Distributed Energy Resources (DERs)[41] and manage the TSO-DSO interaction, it is also necessary to develop and analyse aggregation

[40] Does the consumer have an EV.

[41] Small units connected to the distribution grid with possible two-way flow of electrical power. Common examples of DERs are Distributed Generators (solar, wind) battery storage, electric vehicles (EV) and active demand response (load that can change its consumption to provide flexibility to the system).

models. According to the English Oxford Dictionary aggregation is defined as "the formation of a number of things into a cluster". In a similar way, an aggregator is defined as "a company that negotiates with producers of a utility service such as electricity on behalf of groups of consumers". In this way the SmartNet aggregators take millions of volume-cost bids from homes, businesses and other DER's, packages those bids into larger bid units and submits those bids to a TSO, DSO or some hybrid organization that manages flexibility markets on behalf of TSO and DSO. The system uses bids from a number of aggregators that represent thousands of DERs to clear the market at thousands of nodes. The simulator developed in the SmartNet is based on a Dist-flow AC Optimal Power Flow methodology to minimise system costs, i.e. minimize cost of activation of flexibility bids, while ensuring that network constraints are respected. The solution provided by the simulator yields electricity nodal prices and dispatch volumes for participating DERs over thousands of nodes.

The aggregator agents that are used in this thesis are based on the work of the author on the SmartNet project and particularly the implementation of one of the aggregation models, the Curtailable Generator / Curtailable Load (CGCL) aggregator [79]. This section outlines the design of such a software aggregator agent, and provides useful background on the functional design and operation of an aggregator that is used later in this thesis.

An agent based object orientated design was used to construct the aggregator using a novel finance based buckets or tranche system to aggregate bids across thousands customers. A "bucket" is a term typically used in business or finance to categorize assets, but so far has not been applied in modelling aggregators in the power industry. This approach represents an alternative methodology to the standard designs using optimisation techniques and has been integrated into the aggregator agents.

2.7.1 Functions of an Aggregator

Aggregators are assumed commercial entities, which are profit maximising and will have to provide a number of functions/roles within a real market setting. These will include but are not be limited to:

1. Analysis of customers.
2. Analysis of the market.
3. Weather forecasting.
4. Demand and clearing price forecasting.
5. Risk management.
6. Data management, Accounting and Billing.
7. Congestion modelling.
8. Aggregation of bids (Clustering) with the view to maximize profits.
9. Bidding to Market and Interactions with TSO/DSO.
10. Disaggregation – based on the bids submitted to the market during the aggregation process and results from the market clearing entity, apportion accepted flexibility to individual devices.
11. Notification of any adjustments to individual devices from the disaggregation process.

This thesis is going to focus on the modelling on all elements above except point 7. Congestion management will require an understanding of grid conditions in the areas of interest and would need either real time data from the DSO/DNO or a power grid representation for example in PyPower or Pandapower. To simplify the grid modelling and to focus on the agent modelling side of the simulation, economic dispatch is used to clear the market, so no detailed representation of the distribution grid is provided. Analysis of market and customer data is also performed simplistically in the final simulation.

2.7.2 Storyboarding: How the Key Players/ Agents Interact

A method used in the film industry for presenting a vison or the outline of a film is through storyboarding. Storyboarding is also used by some larger companies to help create visons or to outline future scenarios. They can be used as a common communication technique between disciplines and help design all of the parts of value chain and provide a useful mechanism to allow people that were not present during research to experience a portion of it. For example, in 2012 AirBnB hired an artist from Pixar to illustrate and storyboard their vision [80]. Although vision can be produced visually – there is no reason why it cannot be presented as a script. In the following section, an outline of the interactions and functioning of a market with customers, aggregators and a market clearing entity is provided. This provides the basis for the design of the simulation presented in the following sections.

2.7.3 The Storyboard for Aggregation Business Simulation

Aggregators provide different contract types and services to their prospective customers. They can chose the terms at which they are willing to offer these services e.g. the margins they will charge for the service. Competition between aggregators, will adjust these terms and the services offered. Some customers will prefer one type of contract and others another. Customers will talk/gossip to each other about the performance of the aggregators. They may influence the choice of aggregators in the future. In this simulation, Customers will bid flexibility into the market via these aggregators. They will learn from their experiences about these interactions, rather than just bid their full cost or marginal cost of providing flexibility (a common assumption in literature). Social interactions may also play a part in setting these price levels, as the customers may sometimes share price and contract information via social media. Aggregators will package these bids, so that system operators (TSO/DSO/ISO's) can manage the clearing process in a more timely way. The packaging of the bids provides a mechanism for aggregators to risk manage[42] and to provide additional profits. Algorithms for packaging such flexibility bids will be an important area for future research and provides a mechanism for an aggregator to bid competitively and manage risk at the same time. In SmartNet, bid packaging was considered in the CGCL aggregator agents [9, 82], but was simplified to provide a proof of the concept[43] and could be a valid bucket clustering strategy.

Aggregators would then bid volumes and the weighted average price[44] associated with these bins/buckets into the wholesale market. They may also adjust the bids up or down before doing so. The market would be cleared by the ISO/DSO/TSO and aggregators would be informed whether the bids cleared. Disaggregation by the

[42] Judicious use of the packaging could reduce risk through portfolio diversification (Brearly and Myers [81]).

[43] Bids were spread equally over 10 bins/buckets.

[44] An alternative strategy would be to bid the upper price of the bucket range.

aggregators would apportion accepted volumes at the clearing price[45] to the individual customers. Revenues based the contracts signed with an aggregator will determine the revenues that should accrue to a customer. Good performance in the market will keep customers happy. Depending on contract type, customers will renew their contracts periodically. This thesis assumes contracts change yearly, at the end of a calendar month. Customers may stay with the existing aggregator, change the contract type or move to a different aggregator or leave the aggregation flexibility market system altogether. Aggregators will exit and enter the market as profits wax and wane[46]. New entrant aggregators with new business models might believe that they have a new business model that can outperform existing incumbents. At the end of every year, aggregators will review their performance and consider changing their business models.

Customers in the simulation have emotions (anger and happiness). Aggregator performance will firstly impact these emotions, but social interactions via social media networks will also have an effect. Stimuli from other connected agents will add to the existing emotional view about a particular aggregator. In this model, customers use a combination of social influence, logic (economics of the offers) and emotions to form views about aggregators and their contract offers. This is a departure from most models that take a more rational approach.

At the end of every year, aggregators will select different business models, the basis on which contracts are offered to new or expiring customers. Aggregators choose business models using an economically rational decision framework using historical

[45] Note the thesis assumes that a price as cleared mechanism will be used in the ISO wholesale market.

[46] In the current simulations neither aggregators nor customers leave the market.

price data and volume data as an input. To make this work tractable, only six business models are considered (see section 4.2.6 for a fuller description). One element of this business model will be the extent and methods an aggregator uses to manage risk.

This is a synopsis of the scenario that will be modelled in an agent based setting. Customers and aggregators will be the key agents in this simulation

2.8 Chapter Summary (Key Points)

- Data is currently sparse for distribution flexibility markets in the UK. Use of the current real time Balancing Market is made as a surrogate.
- Analysis of Balancing Market data in 2010's indicates that imbalance volumes are typically centered around zero with a standard deviation of 5% of the day ahead demand. 100% penetration of EV's and Wind could increase this volatility significantly. It estimated that by 2035 this flexibility demand could rise to twice the values seen currently.
- Aggregators will form an important part of a future flexibility market. This chapter sets out the roles and interactions of a potential aggregator operating in a flexibility market. .
- Aggregator and Customer interactions have been outlined using a storyboarding approach.

Chapter 3

Agent Based Models for an Aggregation Business: Assessment and Requirements

The Agent Based Modelling (ABM) paradigm provides researchers with a powerful simulation modeling technique that has seen a number of applications in the recent years including Covid19 modelling, organizational dynamics, transportation and traffic flow, cellular interactions and evacuation (emergency services) dynamics.

ABM is ideal to model systems where the dynamics of the system are too complex to describe globally, but easy to understand locally. ABM is a bottom-up simulation technique where we analyze the global behaviour of the system by simulating the interactions of its individual agents where we describe their individual or local behaviour. Agents can have fixed rules or can adapt according to signals from their environment

The Agents in this thesis' context are generators, domestic and industrial customers and the system or market operators. A number of ABM frameworks already exist for simulating a variety of domain specific instances including for electricity markets. Section 3.1 provides a review of Agent Based Modelling (ABM) in general, and Section 3.2, the power domain in particular, and shows that there are only a few frameworks that specifically focus on the power systems domain and aggregation in particular. Only one, the SmartNet simulator [6] (which is not strictly an ABM model) focusses on aggregators. In addition, none of the ABM systems reviewed takes account, or models, risk, business models or the wider concept of risk management in a corporate context. Section 3.3 sets out the requirements for ideal distribution network flexibility ABM simulator in the context of this thesis. Finally, section 3.4, uses the needs of an ideal simulator to compare existing systems and to select an appropriate environment for uses in this thesis. The structure of Chapter 3 is summarized in Figure 3-1.

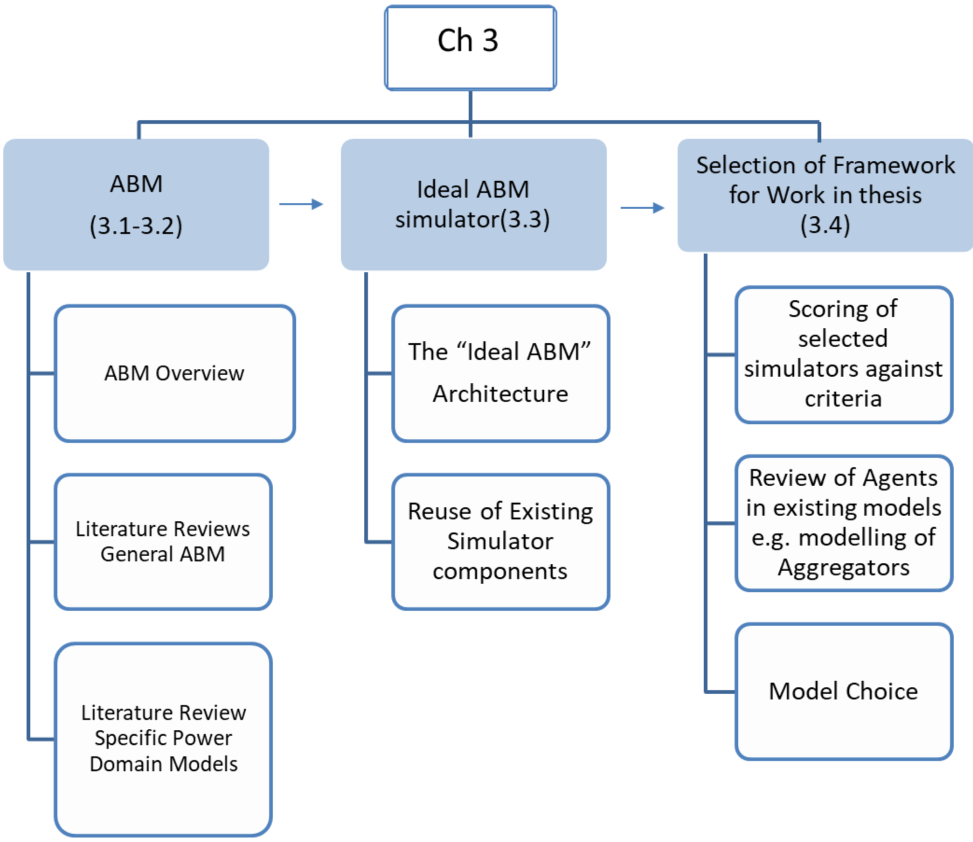


Figure 3-1: Overview of Chapter 3

3.1 Agent Based Models (ABM) and Multi Agent Systems (MAS): An Overview

The idea of Agent Based Modelling was first introduced in the 1940's but lacked the computational firepower to make it a reality. Von Neumann, created simple agents (Cellular Automata CA)[83, 84] and Conway constructed the well known Game of Life [85], a game based on simple agent rules again using CA. Agent based models as they are today, were not introduced till the early seventies. Schelling's "segregation[47] model" [86] introduced the basic concept of agent-based models as autonomous agents interacting in a shared environment. In 1996 Epstein and Axtell introduced their artificial society simulation SugarScape using ABM in the book "Growing artificial societies: social science from the bottom up" [87]. Epstein later introduced the term "generative science" in the book "Agent-Based Computational Models and Generative Social Science" [88], the first in a series of three books. The concept behind these books and associated models[48] is that one can mimic real outcomes using many agents all interacting with simple rule sets. The agents generate the outcomes that mimic real life. The last of these books introduces a framework called Agent_Zero [89] that again uses "simple rules" to generate social interactions to create "realistic social interactions in a number of settings. An adapted version of this framework will be used in Section 6.4 to simulate social interactions between customers and aggregator and this will be the first time such type of framework/model has been used in the power systems domain.

In the Social Science domain, and particularly in modelling complex dynamics in organizational settings, Carey has developed a number of ideas on social interactions

[47] A segregation model demonstrates how individual predispositions regarding neighbours can lead to segregation. Schelling's model was a non-computational ABM model.

[48] Sugarscape is an example of a generative model.

notably within organizations [90-95]. She was involved in the development of the CONSTRUCT framework/software to model knowledge transfer and interactions within organizational settings. CONSTRUCT models individuals groups and organizations as complex systems and uses dynamic networks, agent-based, information and belief/knowledge diffusion simulation to capture dynamic behaviors in groups, organizations and populations with different cultural and technological configurations. This may prove to be a useful framework for modelling organizations like regulators.

During the late 1990's and 2000's, a number of ABM simulation packages, mainly in the Social Science discipline were developed including NetLogo [1], Repast [96-99], MASON [100], JamesII [101], AnyLogic [102] and, more recently, MESA[103]. Many of these systems are written in Java or C/C++, but only a few in Python (e.g. MESA and SPADE[104][49]).

Python has now overtaken Java as the language of choice in Universities. It is a powerful language especially for data science and machine learning. Although it is slower to run than Java, it allows faster code development and is more easily understood and read. Use of C based routines such as Numpy[105, 106] or Xarray[107, 108] can make programs written in Python extremely fast. As a result, developers can spend more time on their algorithms and heuristics related to their chosen subject area. Many researchers are also moving away from using Java, preferring Netlogo[1] and MESA[103]. These are generic ABM frameworks with their roots in social science.

[49] SPADE is actually a MAS system.

For the interested reader introductory texts on ABM and its use in modelling various domains can be found in [109-111]. Leigh Tesfatsion's website [112] also provides useful links to various ABM resources.

3.1.1 Overview of ABM/MAS Literature

There has been a number of surveys on ABM and MAS systems [113-116] as well as many dedicated webpages and tutorials outlining what they can do in terms of Agent Communication Languages, openness, programming language choice and so on. Typically, ABM frameworks focus on a particular area of research i.e. they are specialized to analyse particular features or behaviour, or have other limitations. Only a few specifically focus on power system/market applications. There are now over 70 ABM/MAS systems in existence with a typical lifespan of 4-5 years[50]. Only a few of these systems /designs (e.g. Jade [117], Repast [98])) have lifespans in excess of 10 years.

Frameworks have typically been developed as standalone systems to answer specific questions. Each system has a specific design goal in mind, but for a more general framework. it would be useful to certain combine functions from the various frameworks. Few researchers have joined these systems together or simply reused components from them where appropriate. However, Cardoso [118] in his paper on SAJas (The Simple API for JADE-based Simulations) proposes the use of an API to join Repast to Jade, with a justification that "multi-agent based system simulations (MABS) focus on applying MAS to model complex social systems typically involving

[50] Lifespan in this instance refers to how long the systems have been actively supported. Many are PhD project based and become unsupported once the PhD is finished.

a large agent population. Several MAS frameworks exist, but they are often not appropriate for MABS. Essentially the MAS systems provide superior interaction protocol's between agents over that typically seen in pure ABM systems,, that may be useful in some, especially more detailed settings, e.g. models of EV vehicles communication systems might be better modeled in a MAS setting rather than a pure ABM one. Where this is not the case, an Agent Based Model with a simple communication protocol may be more efficient in modelling the task at hand. In a similar vein, Gormer, et al. [119] propose the JRep framework for simulating an agent based airport scenario, linking Repast (ABM) to Jade (MAS). As they note, "existing agent frameworks focus on either the macro or the micro perspective", but don't combine the two. Combinations of an ABM and MAS architectures may be useful as it will allow us to better understand power system organization/operation.

3.2 ABM/MAS in Power Systems Modelling

Although there are over 70 ABM/MAS models that have been developed since the 2000's, research has shown that there are only around four such electricity/power-focused systems available for power based ABM analysis [32]. TU Delft developed its EMLab model [2-5, 22] originally using Java Spring [120] and the Neo4J database [121, 122] with an aim to aid in European power market policy design. Java Spring allowed modifications to the model via a XML scripting language, but users found it difficult to use and it had a speed impact on the model. The latest version of Java EMLab does not use Spring or the Neo4J database and makes extensive use of Java streams [123] as a form of scripting language. In a separate exercise from this thesis the author has "ported" EMLab into Python so that it can be easily connected to other Python components such as PyPower. It is known as PyEMLab.

Currently, ABMs typically have the following general characteristics:

1. Many agents or actors that represent companies, individuals, power plants, banks, regulators, with differentiated roles and different rules or behavioural aspects.
2. Agents that can learn about their environment and interact with other agents. This can be in passive form with rules that do not change or in an active form using adaptive techniques like reinforcement learning or some other heuristic [124, 125].
3. Some form of agent interaction and communication protocol which defines how agents interact with each other and the environment (see below). Specifically the protocol would define what information is to be exchanged, how often, and between whom e.g. only certain agent's may interact at certain times. In the context of this thesis Consumers interact with Aggregators to change contracts monthly.
4. An environment or environments[51] in which the agents reside. The environments' in this context could consist of a power grid, a power market and a social network. Environments are typically include initial conditions, and background processes, such as market clearing mechanism and power flow calculations.

In ABM, simulated individuals and companies make decisions according to programmed rules, albeit these rules can be adaptable and change. Multi agent

[51] There can be more than one environment and in this thesis, agents exist with a social networks sharing information, as well as interacting with an electricity power market.

systems (MAS) are similar to Agent Based Models but are usually focused on engineering problems. Sophisticated communication protocols between agents not usually seen in ABM are used in MAS so that agents can communicate between each other. MAS are typically considered to operate at the micro level whereas the ABM models are looking at, and modelling, more macro issues. However, for certain types of analysis, it is beneficial to combine both approaches.

Agent Based (ABM) and Multi Agent System (MAS) modelling could provide us with an important arsenal in discovering complex patterns that are likely to emerge from the interactions of a number of players. Essentially, any model of the power system has to represent its physical and commercial aspects, including the grid, the market, the generators, the demand, DERs etc. The model also needs to include an ability to represent and study adapting participant behaviours in companies and customers. Therefore, it is now recognized that a more holistic approach is needed, one that ultimately requires a more sophisticated simulator.

The next section reviews the advantages and disadvantages of various existing ABM/MAS simulators in the context of an aggregation/power simulation wish list.

Power Models in ABM/MAS

As mentioned above, although there are over 70 ABM/MAS systems in existence, few have been developed to address power systems, with categorization and analysis of MAS applications in power provided in [126]. This review summarizes work that has focused on lower level distributed simulation, and also provides a useful breakdown of papers that deal with specific power issues, e.g. markets, generators etc. For example, AMES (Repast) [127-129], ECMAS (Repast) [130, 131], EMLab (Agent

Spring) [2-5, 22], MASCEM [132-134] are specific ABM modelling environments that have power system implementations, while “lower level modelling” of multi agent systems using Presage2[52] is presented in [135, 136]. Furthermore, Anylogic [102], which is not specifically designed for power systems, is a proprietary system that could be used and has an architecture design whose logic allows analysts to model not only agents, but also discrete events and also use system dynamics. The agent behaviours can be modelled using JavaScript, but this is too limiting for purposes of this thesis as it requires a fully-fledged Object Orientated Programming (OOP) language to model complex interactions. More sophisticated agents using Java and Neural Nets, which are linked into AnyLogic using a Java Archive file (JAR), have been developed in [137]. This method requires a greater degree of programmer intervention to link in the various components, and is less flexible than the conceptual design in this thesis.

Furthermore, EMLab, a power system focused ABM, has based its system on the Neo4J graph database [121], rather than a Relational Database Management System (RDMS). Neo4J is an open source/commercial system used by many to analyse Twitter feeds and relationships. It is a very efficient and can be used to store knowledge maps, power networks and, most importantly, the relationships between agents in different layers and between agents on the same layer. It can, in the right circumstances, be faster than a normal database (RDMS) [138]. It can also be used to quickly analyse networks and identify problem nodes for example. Due to its features which also fit nicely with the typical representations of power grids (i.e. they are node

[52] It was designed as a MAS simulator.

based) it may be a useful base for a power system simulator framework.

EMLab currently has code segments (Java) for a CO2 and commodity (natural gas, coal uranium) markets, contract representations, representations of power plants and different technologies within the context of an owning companies that are able to make investments according to market conditions and cashflow constraints within the companies. In addition to generating units and customers, a power link (interconnector) between two countries (Germany and the Netherlands) is also modelled. The power grid that is modelled is heavily simplified.

3.3 An ideal ABM/MAS Power Aggregation Simulation System

In the context of this research, an ideal ABM/MAS power simulator used to simulate the players, power flows and prices in a real time imbalance market providing flexibility would provide the following functionality:

- A design which allows an understanding of how the different behaviours of the various power system agents (generators aggregators, consumers and policy makers etc.) will affect the system technically and commercially. For example, (i) how will power flows across the system change? (ii) how will prices change at various nodes in the system? (iii) will they be too high? (iv) how will generator bidding strategies and demand response impact on aggregation strategies, system operation and prices? (v) Will resulting power flows cause congestion in the system and require new investment?
- Test out new policy rules.

- Try out different agent behaviour techniques e.g. policy agent rules, different agent learning paradigms.
- Allow us to incorporate social networks and customer emotions into the model.

The framework will also need to have the following features:

- Has both a market and network physical (i.e. power flow) layers that are incorporated into market clearing and bidding representations.
- Is extensible and has the ability to switch in and out different simulation layers, roles and change agent behaviours as needed.
- Easy to use.
- Could be solved in distributed manner so to allow analysis of large scale networks.
- Have models of agents representing various actors such as generators, loads, electric vehicles, aggregators, storage, atomic and temperature controlled loads, system operators, regulators, and companies.
- To reuse existing software components wherever possible.

In the context of this research, the use of agents and appropriate algorithms to represent customers (Domestic and Industrial), generators, aggregators and a system operator for market clearing and management. This model must be capable of being easily extended.

3.3.1 Ideal Architecture

These requirements drive us to a conceptual design that would include the following elements shown in Figure 3-2. A system that makes use of principles used in “pure” ABM and MAS systems where appropriate and allows the easy addition of different power domain agent types①[53]. This would include the changing of agent roles/behaviours and an appropriate environment (including power flow simulation, e.g. economic dispatch, OPF) and agents, that are representative of a flexibility market for distribution system flexibility. In addition, there are number of frameworks and examples for modelling emotions, cognitive processes social interactions and representing the psychology of agents [89, 139-153]. A review of these computational social psychology frameworks and emotion modelling is more fully given in Chapter 6 “Human like Customers: Model Frameworks; Emotions and Social Interactions”②.

A framework that would be able to simulate both synchronous and asynchronous agent behaviours to capture investment behaviours and contract mechanisms such as those in P2P[54] transactions③.

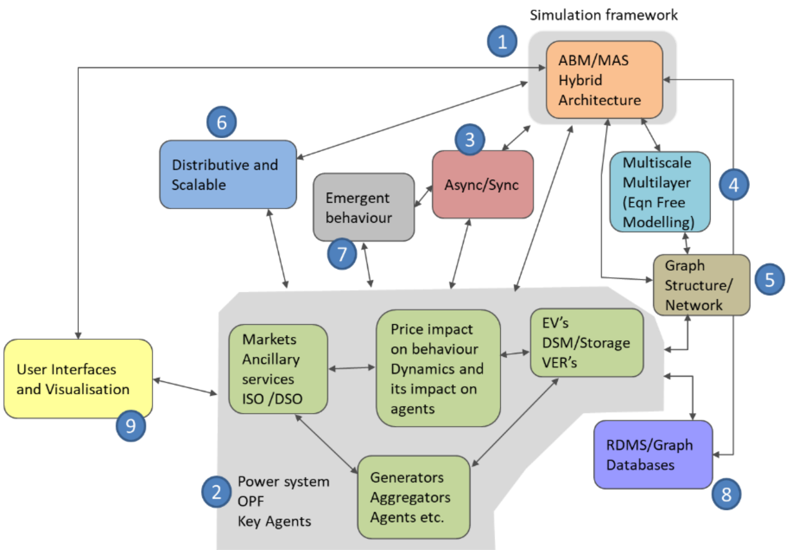


Figure 3-2: Proposed high-level architecture

[53] See numbering in Figure 3-2.

[54] Peer to Peer.

The problem domain under consideration can be represented as a multi layer problem that could be characterized and analysed in coding frameworks such pynet [154] or py3plex [155]. The multi scale nature of the problem domain resulting in short and long term effects, could result in poor computational performance[55]. Equation free modelling [156-161] is a technique that allows researchers to join the micro (short time scales) to the macro level without performing all of the simulation at the micro level improving computational run times. It is analogous to using the ideal gas law equations, which represent the behaviour of gases at the macro level, whilst switching to the micro level of simulating individual molecule collisions as and when necessary i.e. when the macro level representation breaks down④. Some form of graph network structure to represent social media[56] would be essential in this design, so that customer "gossiping" can be represented⑤. The nature of this modelling requires simulation of 100,000's of agents, so a framework that it is scalable and distributed would be a desirable feature in the longer term⑥. Complex systems such as that to be modelled in this thesis would be expected to exhibit emergent behaviour. Detecting such emergent behavioural would be an important part of an ideal system so that further analysis of emergent drivers could be performed⑦. Finally databases for storage⑧ and the use of GUI[57] toolkits like Java Swing [162] or QT [163, 164] to provide user interfaces and visualization will be essential for the long term use of any potential framework⑨.

[55] Long run times.

[56] This is somewhat linked to the concept of multi-layer modelling. Power networks themselves are represented as graphs.

[57] Graphical User Interface.

The main elements of the proposed architecture shown in Figure 3-2 are discussed further in the sections below

Aggregator Functionality: Example - SmartNet – Power System –②

A core element of the ideal design of ABM simulator for this thesis is the aggregation of bids from customers to provide flexibility to the market. The roles that the aggregators should take on are set out in section 2.7. The Python based software developed as part of the SmartNet project [6] is used to look at the impact of different coordination designs on power flows, prices and models millions of devices and thousands of distribution/transmission nodes. It is a generic framework[58] that models an ancillary power market for balancing the system. Although not an agent or MAS based system, it has some interesting features that an ideal ABM system simulator should possess, including that it simulates a large number of assets (current simulation involves 1,000's of nodes and millions of devices), has an optimal power flow simulation (OPF), a bidding structure and methodology, and has a database structure/design suitable for Power. Reuse of such a structure or parts of it, seems eminently sensible, as many hours of development have already gone into this simulator. The SmartNet model uses aggregator agents placed at HV/MV nodes representing transmission and distribution networks in Italy, Denmark and Spain. One aggregator is used to aggregate flexibility from EV's, another from curtailable Load and Generation (CGCL) and so on. There are six different types of aggregators represented [8, 9, 165]. Note in practice actual aggregators may aggregate many different load types not just

[58] The SmartNet Software is a generic model, but currently has models and data for Denmark, Italy and Spain.

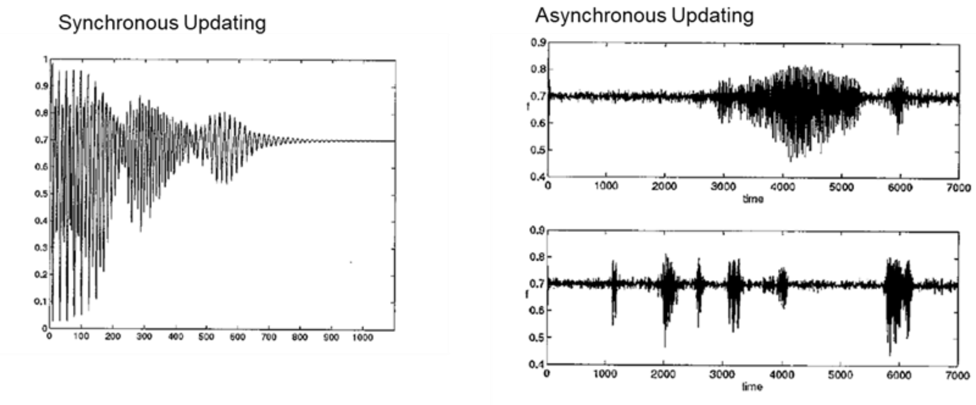
one, so it is somewhat unrealistic. A dist-flow OPF is used to clear the market and provides both nodal and zonal prices. Customers bid at marginal cost[59] to the aggregators. Aggregators "aggregate" these bids per the algorithms set out in [165] and then bid into a clearing market. No strategic bidding or adjustment of the bids occurs. Essentially the aggregator passes on a form of the marginal costs bid by the flexibility providers. Aggregators do not compete with each other. Each of the different types of aggregators uses a different algorithm to aggregate. Although SmartNet is not really an ABM model, the CGCL aggregator has been designed in an agent style and has been reused and adapted in the development of an agent framework .

Asynchronicity ③

A review of ABM surveys and systems shows that ABM (macro level) models are typically synchronous, whereas micro level systems such as Jade (MAS) are typically asynchronous. Asynchronicity in this instance is defined the exchanges of messages between agents intermittently rather than at set frequencies in real-time. Delays between receiving and sending messages can occur and the order in which the messages are sent and received matters to the outcome of the simulation. In this context, Youssefmir and Huberman Youssefmir and Huberman [166] considers multiple agents who take decisions on resource use and act on the system simultaneously in an asynchronous manner to improve their utility. Strategic switching of agents in an uncertain asynchronous environment results sudden fluctuations around an equilibrium (See Figure 3-3) and yields significantly different patterns from that seen

[59] These do not change throughout the simulation and are provided through a database of assumptions.

in synchronous updating. Note in the case of the asynchronous simulation (rhs of figure) that the system is usually stable (moving around 0.7 level) and is punctuated with periods of instability (e.g. at t=3000-5000 and t=6000 in top right figure).



Source: Clustered Volatility in Multiagent Dynamics, Michael Youssefmir, Bernardo A. Huberman 1995 Santa Fe Institute
MAS model simulations – Economics based

Figure 3-3: Asynchronicity impacts on system dynamics; Adapted from figure 1 and figure 5 in [139]

Youssefmir and Huberman's "model attempts to capture the essential features of distributed systems consisting of intentional agents that adaptively react to the dynamics that unfold around them" in a manner somewhat similar to the problem focus of this thesis as it includes learning and adaptive agent behaviour.

Cornforth, et al. [167] discusses MAS agent update strategies using a cellular automata (CA) framework as a case study. They examine updating strategies associated with some real life systems where the agents behave with different asynchronous update schemes and compare this with synchronous updating. The paper provides results on the dynamics of the CA system, under the different update schemes, and shows that the outputs can be significantly different.

In a future smart grid system, peer to peer (P2P) bargaining/interactions will have an important impact both on local conditions and further afield in the wider power system. By their nature these transactions are asynchronous, but other parts of the system will have synchronous interactions e.g. like market clearing. Designing and testing the interactions between these types of system e.g. P2P and the system operator, will allow us to understand how the system might perform in the future. A simulator with the ability to try out different synchronous/asynchronous protocols does not currently exist in the power domain and would be a useful addition to the power engineer's toolkit.

In finance, Jacobs, Levy, and Markowitz [168] developed the "JLM stock market simulator" to look at the effect of asynchronous investments on price patterns. Although written nearly 15 years ago, few authors and simulator designers have taken this approach, which, as they argue, is more realistic. Most of the power system simulators that have been reviewed assume synchronous investments. Of course, it is easier to model and understand synchronous transactions but it is recognized that in the real world, power investors do not act synchronously. Synchronous ABM simulators can be made to simulate asynchronicity by randomizing the order in which agents act. EMLab [2, 3, 5, 22] uses such a randomized approach to model power investments in the market. For example, agents are allowed to invest in the evolving market for power plant provision, but there is a limit to the requirement of such investment each year. By randomizing the order in which the agents invest, different agents will invest in power plant provision in different years. The Presage2 MAS simulator [136, 169-171] also uses this mechanism to simulate asynchronicity.

Modelling asynchronous behaviour especially in contract renewal mechanisms, investment behaviour and P2P interaction could therefore be extremely important. Our problem domain has elements of all the examples cited above. It is, therefore, proposed that any future power simulation environment provide a mechanism to switch between modes of synchronization. However, debugging and validating asynchronous models is extremely difficult. In the case of the proof of concept used in this thesis, we only consider a synchronous model.

Multi-Scale Simulations (Equation Free Modelling) ④

From a Complex Adaptive system (CAS) perspective, emergence occurs when events in one scale (micro) are propagated to another scale (macro) and vice versa. Capturing those effects [172], is key to identifying and understanding emergent behaviour in systems. In the context of the power domain, it is important that system modelers investigate, these phenomena, so that they can design appropriate mitigation strategies. A multi-scale architecture[60] would allow the modelling of these propagation effects. It also fits well with the idea that ABM (macro) and MAS (micro) architectures need to be combined.

However, developing models that can simulate a combination of events that occur at both the hour (for generators, EV's) and the years' timescale (for investments in infrastructure), are typically computationally inefficient. These models require some kind of glue or bridge to join these timescales.

There have been many papers on multi-scale simulations, in recent years, and this provides a potential solution for this specific problem area. However, as discussed

[60] The model in this thesis operates at multi-scales with decisions occurring hourly, daily, weekly monthly and yearly. Currently the model simulates at one time scale ie hourly but different processes are occurring at these other time scales.

above, systems with agents that message other agents such as in social interactions or involve financial transactions are typically “stable” for large periods and are punctuated with bursts of activity. Note the physical power systems themselves may not exhibit this behaviour. Equation free modelling [156-161] provides a promising viewpoint/solution for this particular aspect, and warrants further investigation, particularly in the methodology to trigger the micro level simulation. In this regard, there have been far less papers focused on this specific aspect, especially in recent years. This approach has not been implemented in the power domain and requires further development before it can be used. This thesis does not make use of this modelling paradigm.

Multi-Level Architecture ④

Although there has been growing interest in developing models on multi levels and multi time scales, there still only a few concrete examples [173, 174]. The layered approach is discussed in many papers, but typically as a conceptual model, rather than used as a programming paradigm. This layer or multi-level model also fits well with the conceptual model presented by SGAM [175] for Smart Grid interactions in power.

It seems eminently sensible that any new conceptual design adopts a multilayer structure so that it can capture different views of the system represented as layers in a model (Figure 3-4), such as a physical layer (devices power nodes, flows, congestion), market layer (prices) etc. It also proposed that any new conceptual design allow users to easily add, define or remove layers, to allow experimentation with different designs. This would be easier using a graph database structure as the links in the database would define the layers and their interconnections.

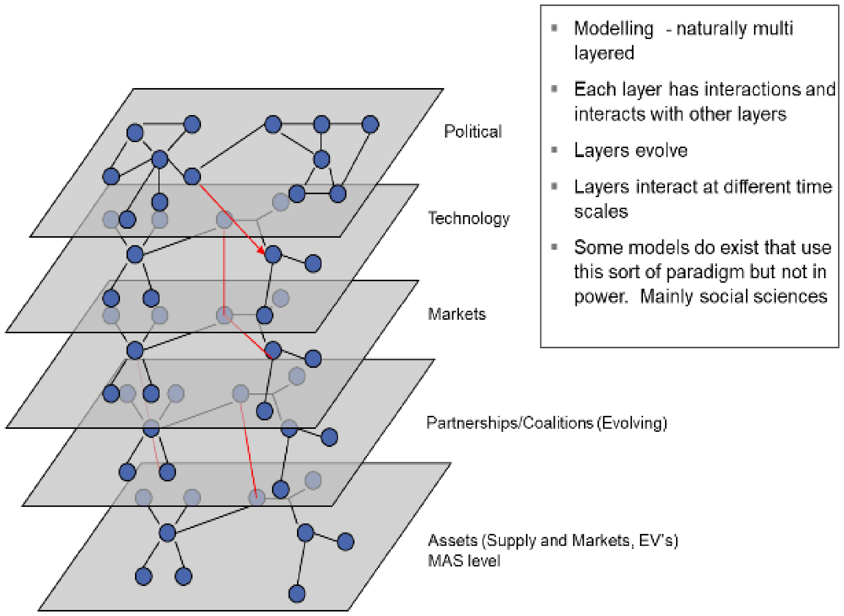


Figure 3-4: Multi-layer concept.

Considering this, one of the necessary features of a new proposed architecture is that it can easily allow changes of the relationships and flows.

It is taken as given that any model in the power domain would also need to represent power flows and be able to "clear" the market on a large scale. This would necessitate that any framework have a methodology and a database structure/design suitable for power distribution networks and particularly for designs associated with the evolving smart grid area and its new participants. Links to existing power system simulators e.g. PyPower, MATPOWER [176, 177] should be considered.

Creating Layers and Agent Behaviours ④

In developing a biology based simulator system Stanner Soffler and Olson [178] developed a component based Python system called ViPER[61], where users can

[61] Later renamed as Vision

combine, recombine and create new biological components visually. Behind the scenes, this system creates Python code which links the various Python classes and modules together. The representation of code and module linkages in defined using a diagram. The Javascript based NoFLo [179] is another framework which could be used as a base for developing an Flow Based Programming (FBP) or visual based coding of agent behaviours. As a library for making complex workflows or asynchronous processes more manageable, examples of its use are in an Internet of Things project drone and robot programming and web design. Representing agents and agent behaviours visually would be extremely useful in the longer term and is left for future development, as this would be a time consuming exercise.

The linking of code segments and agent roles can be achieved in other ways. EMLab's, [2, 3, 22] scripting language also allows linking of components, with the data passed between components using an in-memory repository. This framework is based on a functional approach using Java Streams and lambda functions, which is essentially a functional pipe approach. Here, data is stored and picked up later by the various components. This is the approach that this thesis has taken.

Distributive Computing using Actors: Scalable Lightweight Agents ⑤

An actor is a computational entity that can concurrently transmit a number of messages to other actors, create new actors, and act on the contents of the message it receives. The lightweight nature of actors provides it with a good method to scale and distribute agents and would allow the development of an asynchronous ABM/MAS system using this architecture. Microsoft's Orleans project (2015) [180], uses an Actor based environment for agent interaction, modelled on the AKKA [181] system[62]. It can be scaled as well as distributed, and is also fast. "It reduces the complexity of distributed system by abstracting away concurrency issues together with state management … and reduces the complexity of coding applications by providing a simpler model to maintain object oriented codebase " [182] and would require much less coding than in a system like AKKA. Furthermore, EA Games released a Java version called Orbit (2015) [183] based on this architecture, and its has been found to be very fast. It would be a very useful component linked with other systems to produce an asynchronous based ABM framework. In addition, the original developers of Jade proceeded to develop the actor based ActoDES framework (2016) [184], but it is not clear what the current status of the framework is.

More recently the Python based Ray framework [185, 186] uses the Actors approach. Although it is recognized that scaling and distribution is a long-term aim of a potential framework this thesis will focus on agent design and simulation results.

3.4 The Suitability of Existing Systems

Comparison of the various existing ABM systems against an idea power simulator has been performed using a traffic light system, and is shown in Figure 3-5: Traffic light assessment of an ideal ABM/MAS power simulator. Experimentation with the various systems discussed above has also been performed [63] and forms the basis of the scores presented Figure 3-5 through colour bands.

[62] It is VBNet based eg C++, Visual Basic.

[63] Experimentation with the various systems was carried out to see how they work and whether they were fit for purpose.

	Jade	Orbit/ Orleans	Pressage 2	Repast (AMES)	EMLab	Smart Net
Different agent behaviours - easy to model						
FIPA Protocol						
Multiple networks						
Mobile agents						
Asynchronous						
GIS						
Visualisation/UI						
DSR Modelling - potential and ease to model						
EV Modelling - easy to model or already have						
Storage Battery etc. Easy to model or already have						
Social capital/Psychology - ability to model						
Multi-Layer						
Multi-Scale						
Scale /Distributed						
Holonic/Norms modelling						
Self Org Capability						
Clone agents						
Rule based Engine						
Agents that are required for thesis e.g. Aggregators Generators ISO etc.						
Power OPF - Ability to add						
Graph Database						
Scripting						
Maintained						
Final Score >>>						

Figure 3-5: Traffic light assessment of an ideal ABM/MAS power simulator.

Each row represents a potential need or requirement for an ideal simulator. The table includes some additional requirements that are not specifically mentioned in the discussion in section 3.3.1.that were considered important for the development of the framework presented in Chapter 7. For example, the ability to model self-organization or to have rule based engines. The columns represent the currently available systems that are compared. Scores from 1 – 10 have been given to each cell, with 10 representing that the system fully meets that need. This is the equivalent of dark green in the figure. Zero represents that the system does not currently have that functionality. Colours are provided automatically by conditional formatting in Excel 2016 using a graduated green - yellow – red colour scale. The last row uses a weighted average score to compare the various frameworks. The weights in this example are skewed to those elements that will meet research objectives in the short term. That is, where agent coding, scripting mechanisms are already in use and the frameworks are easy to use[64]. This "simple" scoring mechanism suggests the use of existing power ABM simulators such as EMLab, and or SmartNet.

It is clear from the proceeding sections that there are many useful ideas and components in the existing systems that can be reused, and so would not advocate the complete redesign of a simulation system, but the reuse of large parts of existing simulators (e.g. EMLab, AMES, SmartNet).

By further focusing on specific agents that need to be modelled in this thesis an additional, more detailed "agent" comparison is made in the section below.

3.4.1 Agent Comparisons

Various types of agents are modeled in the current power domain ABM's. Many

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[64] None of these frameworks are particularly easy to use and will require significant investment by researchers to become operationally proficient.

of them include the core agents and environments that are required by this thesis e.g. load serving entities, generators, traders and market operators that clear the markets. For example, in addition to the core agents, EMLab [2-5, 22] models CO_2 and commodity markets that providing an impact on the energy costs of the generators. On the other hand, the SmartNet simulator [6-9, 165] also models aggregators, which is of a particular interest, since this thesis focuses on the Aggregators and their customers.

As a starting point for the work presented in this thesis, a review of the AMES, EMLab, SmartNet and Presage2 systems has been carried using literature [[2-9, 22, 127-129, 165] and by experimentation with the various systems[65]. The results of this review are summarized in Table 3-1 below, in the context of their use in simulating aggregation in the power domain.

ABM >> / **Function**	**AMES (Repast)**	**EMLab**	**SmartNet ***	**Presage 2**	**Comments**
Programming Language	Java with API to Python PyPower [187]	Java	Python	Java	Presage 2 was designed as a MAS simulator
Aggregators - Models	X	X	√	X	

[65] Note systems like MASCEM and others are not currently adequately supported and have been excluded from this review.

ABM >> / Function	AMES (Repast)	EMLab	SmartNet *	Presage 2	Comments
Optimal Power Flow (OPF)	Simple representations with link to PyPower [187] Small Networks	X Uses Economic dispatch and clearing across multiple markets with inter-connector capacity constraints	√ Large Networks modelled with 1,000's of nodes	Links to MATPOWER in some models. Generally small networks modelled	SmartNet uses PyPower[187], PowerGama[28, 29] and its own SOCP simulation to perform OPF calculations
Aggregator risk	X	X	X – Has single input value in data structure but not currently used	X	
Aggregator Business Modelling	X	X	X	X	
Aggregator Corporate modelling and Detailed Profit & Loss (P&L)	Simple model for profits – used to exit industry	Model for profits, and cashflow, used to constrain investments in new plants and technology. NPV and Cashflows	X	X	
DSO/TSO interactions	X	X	√	X	
Social Network Interactions	Repast can be used to perform social network analysis and simulate social science ph.	Diffusion of light bulb technology using small world network methodology [188]	X	? Has ability to model network structures and interactions.	

ABM >> / Function	AMES (Repast)	EMLab	SmartNet *	Presage 2	Comments
Generators	√	EMLab models power plants as part of generator companies and provides cashflows at the corporate level which is used to effect investments		√	All model Generators to some degree
Customer Psychology and emotions	X	X	X	X	Computational psychology solutions exist in the social science domain. See Chapter 6 of this thesis later for a fuller discussion
Industrial customers	X	X	X	X	Detailed industrial modelling is not currently carried out by any these models
DSR	?	X	SmartNet assumes that customers bid at marginal cost. Fixed during simulation	X	
Domestic Customer Variable bidding (Flexibility) With learning	X	X	X	X	EMLab does provide bidding at the plant generation level but not at the customer level. Forecasting is made internally of future prices
Database (Connections and management of)	CSV for input/output	CSV for input/output	PostgreSQL SQLite3 Using Django ORM	PostgreSQL Mongo CSV for input	

ABM >> / Function	AMES (Repast)	EMLab	SmartNet *	Presage 2	Comments
Other Functions		Scripting language to add roles to agents Has used Neo4J Graph DB. Original EMLab used Java spring Aspect Orientated programming paradigm which allows layers and code segments to be weaved in and out of the code using scripts			

Table 3-1: Comparison of existing systems; their capabilities to model aggregators and dynamic customers

**SmartNet is not really an ABM simulation platform but the Curtailed Generation Curtailed Load (CGCL) aggregator within the simulator has used agent based principles in its simulation of the aggregator.*

Note GridLAB-D™ [189-191] "was developed by the U.S. Department of Energy (DOE) at Pacific Northwest National Laboratory (PNNL) under funding for Office of Electricity in collaboration with industry and academia and is a first-of-its-kind time-series power distribution system simulation and analysis tool that provides valuable information to users who design and operate distribution systems, and to utilities that wish to take advantage of the latest energy technologies. It incorporates advanced modelling techniques with high-performance algorithms to deliver the latest in end-use load modelling technology". It is a detailed model with physical and abstract representations of various grid components and has an abstract ABM component. The current version is a commercially robust platform developed for DSO's in the USA, but could be used in a UK context. It lacks in its ability to model human interactions in this system. Investigation into the linking of the AMES ABM platform to GridLab-D has also been performed [192] and HELICS has been used as Co-simulation environment to run GridLab-D [193]. It is currently written in C++, but at the time of framework selection did not have a python interface[66]. It is understood that a Python interface may now exist, but that C++ programming experience is still required to work with the system. For this reason it has been removed from the system selection.

All of the above models would be able to incorporate any future aggregator design with dynamic customer (domestic and industrial) interactions into their frameworks. However, Table 3-1 indicates that none of the systems adequately model:

- Aggregator risk.
- Corporate business models (Aggregator specifically), but companies in general.
- Customer psychology in the power domain. Note much progress on the modelling of computational psychology (emotions and cognitive ability) front in the social sciences has been made (see Chapter 6) and an incorporation of some of these elements, would be a useful addition to ABM models in the power domain.

[66] See discussion https://sourceforge.net/p/gridlab-d/discussion/842561/thread/a39de4ac/

- That although some models make use of social networks, many of these frameworks are in the early stages of development. "Gossiping" about prices or aggregator contracts and aggregator performance has not been modelled in these frameworks.
- That EMLab and SmartNet provide many of the elements that this thesis requires for modelling aggregators in a distribution flexibility setting.

3.5 Chapter Summary

This chapter introduced current research on ABM especially for simulation of electricity markets. It presented an initial scope and ideas for an "ideal simulator", including reuse of ABM frameworks, asynchronicity, visualization, multilevel and multi scale modelling graph networks for social media modelling. Although, it a longer term aim to design a framework with these various aspects this thesis will focus on reusing the EMLab and SmartNet software framework (in a synchronous mode). Output from simulations will be stored in external databases for later analysis using other tools like Excel and SPSS [194].

Key Points

- Few ABM systems model aggregators in the context of a future electricity flexibility market. Those that have (e.g. SmartNet), have assumed that customers bid at marginal cost, and have no learning.

- Risk is not modelled and no detailed representations of aggregator's cashflows including the use of different business models is present. These models do not include customer's emotions or represent social interactions in their formulations.
- More importantly, the interactions between aggregators in a competitive environment and with their customers, has not been modelled. This will be the focus of this thesis.

Chapter 4

Aggregator Business Models: Costs; Profits and Future Views

This chapter provides a review on the current business models used within the aggregator business in the UK, Europe and the USA. Brief introductions to business modelling are given and literature on electricity market aggregation business models are reviewed. The majority of the current literature focusses on current business models, so this Chapter explores the use of other techniques and industry analogies, to develop future business model views for aggregators. Little detail is currently given on the exact mechanics of an aggregator business nor the cost structures of operating one. This chapter therefore develops some revenue forecasts as well as costs associated with an aggregator in the future. These have been used to construct an economic model, which has been used to explore the profitability of operating such a business. Literature and evidence from analogous industries indicates that future business models will become more service orientated and would use revenue streams from diverse parts of the energy chain. Incremental development of such business models is likely especially where incumbents are concerned but the threat of disruption from companies like Google; Amazon; IBM and so on is large. To facilitate simulation of business models effects in an ABM framework, six business models based on a two-dimensional framework (risk stance vs revenue generation model) is developed. This model is also used in Chapter 5 to evaluate risk in an aggregator business. The structure of Chapter 4 is summarized in Figure 4-1.

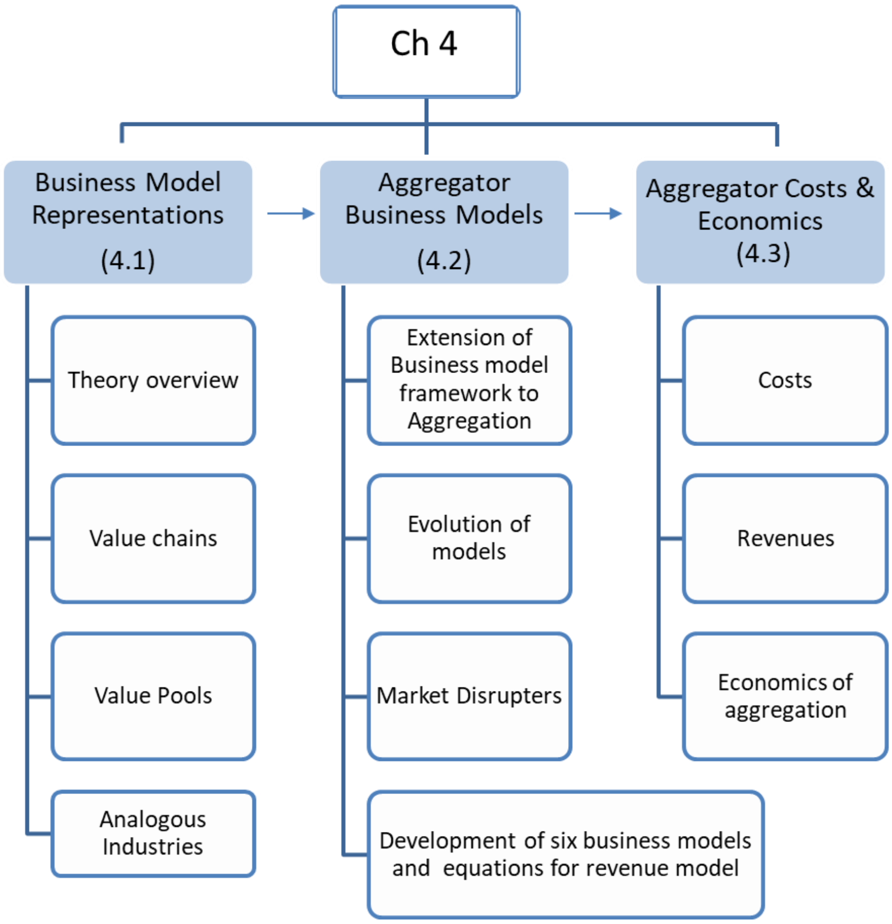


Figure 4-1: Chapter 4 overview

4.1 Overview of Business Models: Approaches and Industry Analogies

Before revenues, costs and the risk associated with an aggregator business can be estimated, definitions of the aggregator's mode of operation or business model has to be given. The business model provides a blueprint on the methods by which an aggregator will position itself to make money. In the next section a review of the approaches used to identify business models is given along with a review of analogous industries to highlight potential profit margins and other issues.

This is followed by a review of the literature on specific aggregator business models. Finally using structures discussed in this chapter a business model framework is developed for future aggregators. This model is used in simulations presented in later chapters.

4.1.1 Overview of Business Models: Literature Review

The Cambridge dictionary defines a business model as "a description of the different parts of a business or organization showing how they will work together successfully to make money". Zott, Amit and Massa [195] review business model approaches and find that there is a multitude of approaches using methods such textual, verbal, and ad hoc graphical representations. There are a multitude of definitions of what a business model is and the term "business model is used with different meanings .. partly because of the absence of consensus on the definition of a business model and partly because of the different contexts in which the term is used" [196]. "A common formulation of the term is as a description of the way a firm does business at the strategic level" [197](p. 14).

4.1.2 Value Chain Approach

Value chain analysis is still a sound model for identifying market opportunities and competitive differentiation. Originally developed by Porter [198] in 1985, it is still widely used in many corporate settings although Porter's original framework has been modified or is used in conjunction with other methods. Osterwalder [199, 200], developed a comprehensive template on which to construct business models. The nine-part "business model canvas" is essentially a way to lay out assumptions on key resources and key activities in the value chain of the business, but includes customer relationships, channels, customer segments, cost structures, business partners, revenue streams and the value proposition. Adner [201] takes quite a different approach from most business model researchers and develops the idea that business models should consider the role and interactions of the business model in the wider ecosystem. He uses such a framework to look at Apples Ipod model and the EV battery business "Betterplace" [202] in the context of a wider eco system.

It is important to recognize that value will ebb and flow over time, it will move from one part of the value chain or pool to another. How fast it moves will depend upon competition between entities and the dynamics present in the market. Different business models will fare better than others at different times as the dynamics of the market change both in terms of customer mix, volumes and prices.

4.1.3 Value Pool Approach

The "Value Pool" approach attempts to identify where profits or value will be created in particular business segments in the future. Gadiesh and Gilbert [203] developed the concept of identifying profit pools in an Industry's value chain in 1998, but van Beek et al. [204] coined the phrase "value pool" later to recognise that a profit pool analysis needs to be considered in the context of business models. Business models therefore capture some or all of the value in the profit pool. The business model essentially defines how these businesses will extract value from the pools identified. Slywotski's Value Migration [205] approach is somewhat similar in that recognises that value chains evolve and profits within the value chain shift through time[67]. Positioning to take advantage of these movements is key.

4.1.4 Analogous Industries Approach: Industry Analysis: Margins and Deregulation; Business Model Evolution in Newly Formed Markets

Analysis of the evolution of gas marketing in the US since pipeline deregulation in the mid 1980's, shows how operating margins have fallen with time (see Appendix A.2 and A.3). As a result, and in order to maintain profitability and market-share, US gas marketing companies[68] consolidated and diversified their range of services that they offered. They now provide such services as; Supply aggregation and procurement, balancing, capacity reservation, storage facilities and risk management services. Current business models of the aggregators in the power domain are focused on a single dimension, but would be expected to evolve maybe along the lines of the gas industry.

Studies of analogous industries (Appendix A.3) have shown that margins are eroded with the introduction of competition, especially after deregulation or the introduction of new regulations, and generally follow an exponential decline, eventually stabilising in the range of 2-5%. Initial margins may be in excess of 20%. However, in the early years after deregulation losses can occur. The time taken for margins to reach this low profit margin range is variable, depending on the industry, but it can be as short as 1-2 years. In the US gas market, it was 8 years before operating margins fell below 5% (on average), whereas in the UK the time period was

[67] Slywotski's approach is not strictly a value pool approach.

[68] Known as gas retailers in the UK.

much shorter, of the order of 4-5 years. It is likely that margins in both the domestic and industrial flexibility markets will fall to similar levels, ie 2-5% as competition heightens. The evidence suggests that new aggregation services are likely to follow the same fate. Business models will evolve and new services will be offered somewhat similar to the experience in the US/UK gas and power retailing business of the 1990's and 2000's.

In many industries there appears to be a link between the operating margin and market share with higher margins associated with larger market share [206]. This also appears to be the case in the energy retailing business. The same would be expected of a new aggregation business in the UK or elsewhere.

There is no justification for marketers to earn large margins where they are taking little or no risk, e.g. buying off the spot market and selling on with a small profit margin of 0.5-2%[69]. For those taking more risk, e.g. by wholesaling and repackaging, it is estimated that on average the companies should be earning 7-14% profit margins based on the performance of companies like Centrica (British Gas) (see Appendix A.2)[70]. Power Aggregator companies are essentially businesses that are repackaging bids from customers and will need to have a good working knowledge of different services that could be offered, if they are to survive.

Losses in Analogous Businesses

The analogous industries analysis (see Appendix A.3) does not bode well for power aggregators. Analysis shows that companies are prepared to make losses for up to 5

[69] Large oil trading companies like Trafigura, Vitol have margins in the order of 0.5%.

[70] Note this is consistent with results from an analysis using a CAPM based framework – see section 5.9.3.

or 6 years, or even longer. Teweles and Jones [207] also provide evidence that trading companies typically lose money 3 years out of 4. However, in all these examples the period of loss is generally related to the particular business cycle of that industry. One would expect therefore, that in the power aggregation business where many companies may effectively be underwritten by financially strong parents, e.g. the large power companies banks or the likes of Amazon, may continue to make losses for longer periods. However, smaller companies will find it harder to survive. Although the UK energy retail Industry made low profits as competition heated up, exits from the industry and other effects helped profit margins to rise [208].

Analogous Industry Models

Johnson [209], like many authors in this research area, provides a list of analogies based on experiences and patterns extracted from other industries including models that he gives quirky names e.g. Brokerage bundling; the affinity club; cell phone model; crowdsourcing; freemium: fractionalisation and so on [210]. Slywotzky and Morrison [211] analyse profitable companies and also look for patterns in those companies and the industries they operate in. They develop 22 profitability models that they characterise using three dimensions (strategic, operational and organizational) with many more sub dimensions below each category.

4.1.5 Aggregator Costs: An Important Driver of Aggregator Profitability

An important element of modelling a commercial aggregator will be to model its finances and its profit and loss account. Commercial aggregators will need to be profitable and cashflow balances will influence whether the company exits from the industry as well as potentially impact on bidding strategy. An important component of any cashflow model is the cost model.

There is a currently no known detailed cost analysis of commercial aggregators in the power industry, although some accounts are available for so called aggregator companies in the UK and the USA These provide some information but lack in detail and assumptions of key parameters including detailed descriptions of the business model in use.

Using the author's experience on aggregation costs in the US/UK gas and power Industry, SmartNet [212], and data and views extracted from conversations with Industry Professionals, a bottom up cost model of different operation models has been developed. Operating (OPX) and capital costs (CPX) have been estimated for a number of items and costs built up from individual components (for more details see excel spreadsheet at https://github.com/Ghoworth). A key function of the SmartNet project was to develop a cost benefit analysis for the project, including the cost of developing key parts of the software required for operating an aggregator. Using some of this work and using the author's prior experience from the trading business and literature searches on the cost of accessing data, a spreadsheet was initially created for a business with 150,000 customers. This includes line items for various costs such as office space rental, business licenses, computers, software and staff. The cost spreadsheet was further modified to take account of different number of customers. For example, from experience it is known that one account executive could look after say 1000 customers. Users of the spreadsheet can change these assumptions. Maintenance costs of software packages are assumed to be 20% of the initial capital cost.The model has an accuracy of a class 4 estimate (+- 30%) [213].

Note that within a particular business model, aggregators could use different risk strategies and revenue models. This may have a small impact on capital and operating costs but these are ignored in the analysis below. Figure 4-2 and Figure 4-3 summarizes the capital (CPX) and operating costs (OPX) of an aggregator providing flexibility in one area (e.g. a city and surrounding areas) and on one product aggregation service. It is based on a bottom up cost estimate, with a number of components shown in the figures.

Software and Hardware

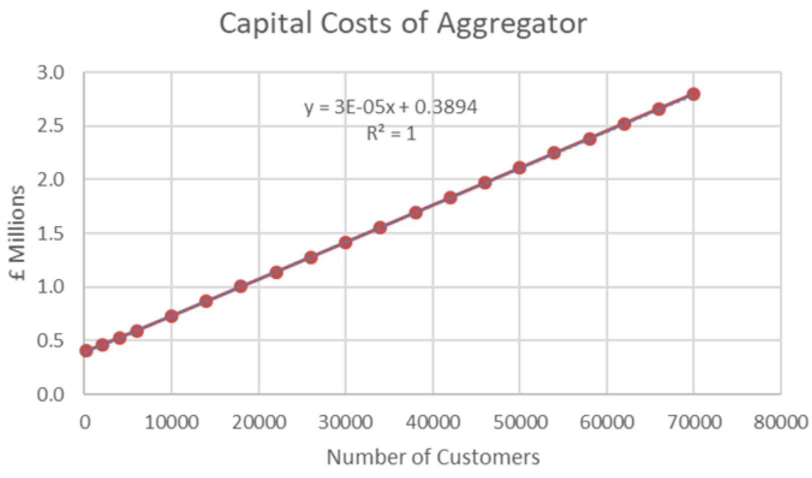
Description	Cost £	On off	Man months	Comments
Home Automation and Harware Control and comms equip	12,000,000	1	0	May be able to spread costs over a number of years have assumed one year hit
Accounting package bids and balancing	360,000	0.75	18	might be able to buy this on an annual basis and pay like 50k/year - that's the equiv of about 450k capitalised. Assume 1.5 people for 12 months including all testing and debugging.. Utilidex accounting softare - cpauitalised comes out around 400k
Accounting package Finance salries payroll accounting SAP	416,520	0.75	21	SAP core ERP finace software captilised - costs 150 per user/month - plus add ons say 20 users
CGCL package	450,000	1	23	Will depend on how complex this is - probably 4 months - to 15 months of work and testing
Risk management add on	720,000	0.8	36	Based on experience of developing actual risk management system
Clearing Pricing model/OPF	£ 2,100,000.00	1	105	Essentially my quick estimate odf what I think it would cost to build peters clearing model again - We would need a view on prices and might do this say using pattern recognition - or some simplified version of peters model - but if I were an aggreagtor i would need to know how the network is going to behave and what the prices look like. might be able to do this for 200k if simple system
Congestion model DX	240,000	1	12	Need to really understand how Congestion might affect me as a bidder - especially if im responsible for the rebididiing and taking additional costs on congestion
Weather forecasting	240,000	1	12	
General software				
IT servers and software				
Server	£ 6,666.67	1		One off charges
Laptops	£ 29,333.33	0.6		""

Figure 4-2: Capital cost of an aggregator – bottom up assessment

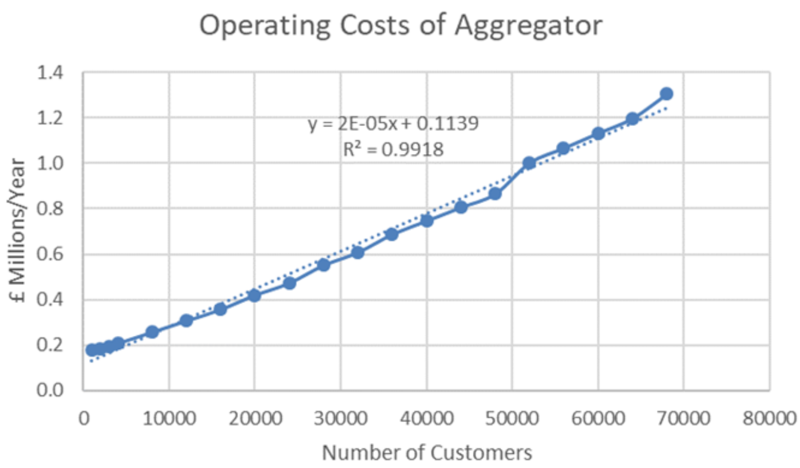
Costs per Year		
The purpose of this spread sheet is to provide a high level cost and process time estimate for a commercial aggreagtor of some complexit		
General Infrastructure	Cost	On or Off/Ratio
Licence for being an aggreagtor	£ 50,000.00	1
Rent for space	£ 26,666.67	0.75
IT hardware	£ 24,000.00	0.75
Comms phones etc	£ 4,320.00	0.9
Salaries		
Salaries - circa 160+10 people	£ 910,000.00	0.75
IT servers and software Maint		
Accounting package bids and balancing	£ 72,000.00	1
Accounting package Finance salries payroll accounting SAP	£ 83,304.00	1
CGCL package	£ 90,000.00	1
Risk management add on	£ 144,000.00	1
Clearing Pricing model/OPF	£ 420,000.00	1
Congestion model DX	£ 48,000.00	1
Weather forecasting	£ 48,000.00	1
Server Maint	£ 1,333.33	1
Laptops	£ 9,777.78	0.75
Optimizer – multi dimensional – MILP NILP LP and genetic evolvers	£ 1,000.00	1
Office Software	£ 2,133.33	1

Figure 4-3: Operating cost of an aggregator – bottom up assessment

Figure 4-4 shows how capital and operating costs are predicted change with the number of customers.



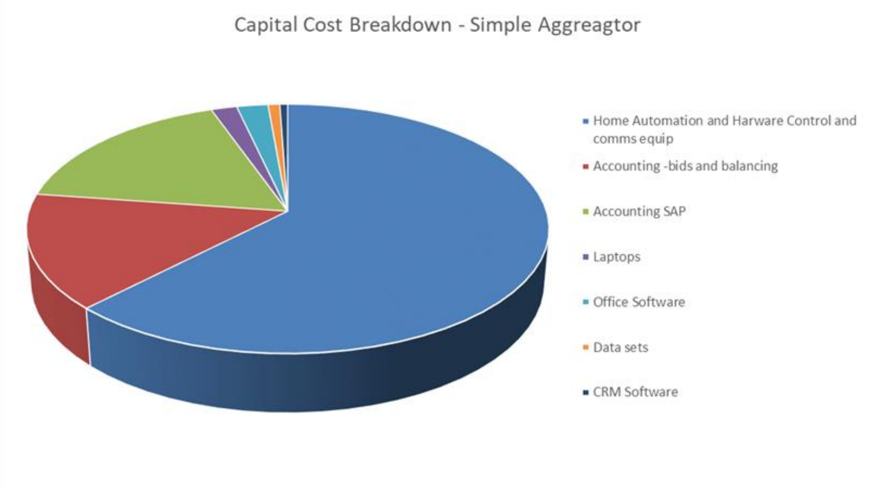
(a) CPX by numbers of customers



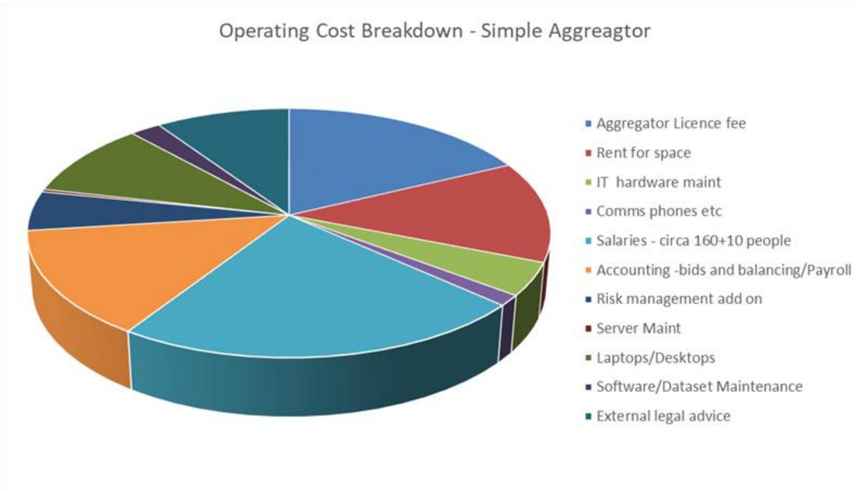
(c) OPX by number of customers

Figure 4-4: Cost of an aggregator; Variability with customer numbers

Figure 4-5 shows the breakdown of costs for an aggregator with 10,000 domestic customers. Note that around 65% of the capital costs are associated with home automation devices. It is assumed that the aggregator would provide such equipment to automate flexibility provision. Accounting, bidding (market interaction) and control software (Virtual Power Plant software) makes up another 25%. In the case of operating costs, categories are more evenly distributed but salaries and maintenance costs (software and hardware) make up the bulk of these costs.



(a) CPX – Distribution of Costs



(b) OPX Distribution for 10,000 Customers

Figure 4-5: Aggregator cost breakdown

4.2 Aggregator Business Models in the Power Domain

The MIT utility of the future study [214], in the context of their work defined an aggregator as "a company that acts as an intermediary between electricity end-users and DER owners and the power system participants who wish to serve these end-users or exploit the services provided by these DERs." Retailers are therefore a special class of aggregators that (historically) served only the function of aggregating small electricity consumers—residences and small commercial entities—and procuring power on their behalf."

Current aggregation business models [215-217] in the sector are relatively straightforward typically using a margin based fee model[71], however, it is reasonable to expect that business models will inevitably evolve over time. To evaluate that change, it is important to consider the following key research questions:

- How will business models evolve and what business models are likely to prosper and under what conditions?
- Do these models need regulator support and in what form?
- How will customers react to aggregator offers and what will aggregation take up be?
- Is aggregation good for consumers?
- How to fairly allocate social welfare resulting from DER flexibility?

The figures of [214] (in Appendix B of this reference) provide a good breakdown of how companies are currently situated mainly in the US and European markets[72]. Figure 6.4 (reproduced in Figure 4-6) in the same report provides a useful view of how aggregators might progress from the current state to a risk managed "fundamental aggregator" state that includes economies of scale and scope but gives little detail on exactly what this will look beyond a general statement.

[71] For example, a percentage of revenue obtained from selling services

[72] 22% of the respondents were situated in Europe/Israel;78% in the US

Scope in this instance includes “required services for or from a customer (e.g., energy, operating reserves, voltage control, etc.), rather than having multiple aggregators that each procure or deliver a single service. Economies of scope and product bundling are present not only for electricity services but also for adjacent sectors that supply heating, gas, energy efficiency solutions, telecommunications, or Internet services”

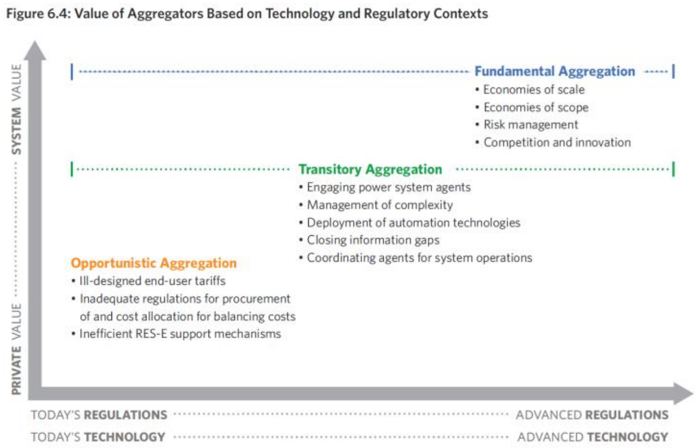


Figure 4-6: Reproduced from [214]Value of Aggregators and regulatory contexts

BestRes [218] reviews current aggregator business models in European markets including the UK and considers models such as Combined aggregator-supplier, a combined aggregator-DSO model and so on based on existing companies business models. There is a section on revenues and costs but little detail, is given.

An analysis of Companies House submissions by various UK aggregator companies [219], using account notes, profit and loss accounts (P&L) and balance sheets provides us with some data on the performance and costs of their businesses over the last 2-5 years. This data indicates that many aggregators based in the UK are using a margin-based model where aggregators are charging clients ~30% of the revenues that the customer's assets generate – a simple margin model[73]. Many of them are currently not profitable. Costs associated with these companies are typically software and Human Resource (HR) based[74]. Companies in the UK appear to be paying around £1 million for software that is being used to manage the aggregation process. These numbers concur with the bottom up analysis of costs that have been derived above and the figures shown in [212].

A review of energy service orientated business models was carried out by Hamwi and Lizzarralde [220] in their study on 30 business models as reported and reviewed in a variety of energy based journals. By clustering the models they identified that there were three general business model designs[75] in the energy business. These were:

- A customer owned – product centric model – Customer buys, uses assets and sells output
- Third party service centered managed model - Third party may or may not own the assets, but generally manages them
- An energy community based model (e.g. P2P[76]/ shared community assets)

The study seems a bit limited in the context of this work but provides another classification of potential business models that may be useful.

Keisling's work on a new paradigms in rapidly evolving electricity markets like the

---

[73] Authors estimates from the accounts.

[74] From an analysis of their accounts and associated notes by the author.

[75] Note this a clustering exercise on business models presented in journals and does not include future business models or those that have not been reviewed in journals. By their very nature good business models are likely to be kept confidential.

[76] P2P is not the only community-based model that could be used here. This is used as an illustration.

UK and the US [221, 222] present views on the uses of digital platforms such as Uber, Air-BNB to provide P2P services as well as in electricity retailing. It recognizes that very different approaches to the current business models in the power sector may be more useful to customers. They are likely to be service and customer orientated and based on a digital platform. Note it is recognized that these P2P and digital platform providers could present important alternatives to the market. This thesis will focus on "pure aggregators" but future work would include these alternative business models.

Work by van Beek's [204] looks at opportunities associated with a low carbon economy and develops two business models. The first highlights the need to focus on companies that provides energy as-a-service, i.e. delivers energy services to customers instead of a commodity. The second, a business model that provides access to local low carbon energy by collaborating with communities and individuals.

Analysis of aggregator models in [223] suggests that "commercially successful aggregation models generate a diverse income from multiple revenue streams. Furthermore, the results indicate that aggregators can make complex aggregation business model more appealing to potential customers by combining several market roles". Companies operating in analogous markets have learnt similar lessons and successful participants typically have a multi-dimensional business model combining several roles (Appendix A).

P2P Business Models (GO-P2P Framework)

Peer-to-peer (P2P), and transactive energy markets offer new business models for local energy trading and could be both part of and a competitor to aggregator business models. Over the past five years, there has been significant growth in the amount of academic literature examining these local energy markets. There are few pilot projects (e.g. [50, 59]) in existence but this is growing. Reference [224] provides a literature review of 139 peer-reviewed journal articles and examines market designs in these systems and was carried out as part of the work of the Global Observatory on Peer-to-Peer, Community Self-Consumption and Transactive Energy Models (GO-P2P) programme.

GO-P2P [225-227] is an international platform that aims to give governments, business, and non-profit organizations the data they need to assess the advantages and disadvantages of smart local energy systems like P2P in their individual nations. The idea is that "lessons learned from these pilots will form the basis of an international comparative analysis, aiming to provide an assessment of the key factors enabling or inhibiting the rollout of P2P models across the world.

Some of the key emerging insights from this work include[77]:

- There are numerous ways to develop local energy trading systems and they provide a wide range of social, environmental and energy system benefits.
- Policy makers and regulators should set clear outcome priorities to guide market design.
- Local energy trading systems can reduce grid constraints.

[77] See [225] for additional insights.

- “Local energy trading is likely to work better under multiple supplier models (i.e. where one consumer can have both a local and a national supplier)”.
- The energy regulatory system has to recognize small participants, such residential customers, as market actors in order to be widely adopted.
- These systems will require high levels of automation. Note automation is abstracted in the work of this thesis and is assumed to be present.

Although this thesis will focus on the provision of flexibility by aggregators via for example a virtual power plant digital platform, it is important to recognise that other models e.g. P2P, will need to be considered. Indeed future work should look at how P2P and other models will work together in any future marketplace.

4.2.1 Value Pool Approach in the Power Domain

The value pool approach has been used by Wegnera et al. [228] to look at value pools in the UK energy power market in a number of future scenarios. Pool 2 (energy service provision) and pool 5 (flexibility optimisation) speaks directly to the aggregator concept discussed in this thesis, and were identified as key value centres in this work. New revenues associated with these pools is estimated at £2.5-£14.8 Billion[78] (2023 real terms) in 2050 in this paper.

Hall and Roelich [229] again use the value pool approach to identify potential business models for a future UK electricity supply business. Nine “high level” representative local supply business models are identified and their value propositions,

[78] Escalated from 2015 to 2023 terms.

value capture methods, and barriers to market entry are analysed. These competing models include local aggregation, Peer-to-Peer (P2P), a not for profits model and the current energy retailing model. Demand side response participation is seen as an important opportunity in this regard. They recognized that customers do not necessary focus on economic but on environmental and social aspects as well. Table 2 in the paper scores the models against the opportunities identified in the paper using a simple "+++" to "---" scoring system . A simple count of the plus symbols reveals that the multiple utility service provider (MUSCo – multiple utilities within same contract) and the local aggregator model are the best according to this scoring mechanism. However, certain customers are likely to have a natural affinity to certain business models. The paper focuses on the high level aspects of the various models so no detailed views are given about aggregators business models and or costs.

4.2.2 Business Model Economic Impacts

Company and financial objectives will have a great bearing on the way that an individual investor, the aggregator in this instance, will view the world. Minimum hurdle rates (i.e. meeting IRR[79], NPV/I[80] and or other measures) will be a key determinate of aggregator investment behaviour. Risk will play its part too, as volumes and prices will be uncertain, but in initial modelling, this could ignored.

Company financial objectives and economics would be affected by views on potential revenues as well as the cost of running such a business under different

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[79] IRR – Internal Rate of Return.

[80] NPV – Net Present Value; I- Investment. NPV/I is net present value per unit of investment.

assumptions. De Clercq et al. [223] reviews six current business models/market roles used in Europe (2018), and presents some high level economics based on the analysis of case studies on the markets roles. This includes a model using solar PV assets as well as managing distributed generation in apartment buildings. Financial performance of different trading strategies are given (£/MWh basis) for different portfolios of assets. But no detailed analysis of costs was carried out for these aggregator models. Future business models are not considered in this paper and there is a lack of data or analysis on the cost structures of future aggregator business models.

In the context of the aggregation business, customers will want different service offerings that fit their particular needs, but ultimately would like to reduce their energy bills by supplementing income from providing and managing flexibility. This fits well with the ideas that Hall and Roelich outlined in [229]. Some customers will want to be actively involved. Others will be happy to delegate this function ultimately to the aggregator, while some may not want to participate in the aggregation market at all.

Aggregators will want to make money from these interactions, manage risks associated with such a business and to do this as cheaply as possible.

4.2.3 Extension of the Business Modelling Approach to this Domain

Although there are a multitude of different business model approaches they each provide a different set of lenses in which to view a particular Industry. Using a combination of these approaches, a multidimensional model (Figure 4-7) based on exhibit A1.2 in [211] has been derived to consider the types of business model that an aggregator business model could follow in the future.

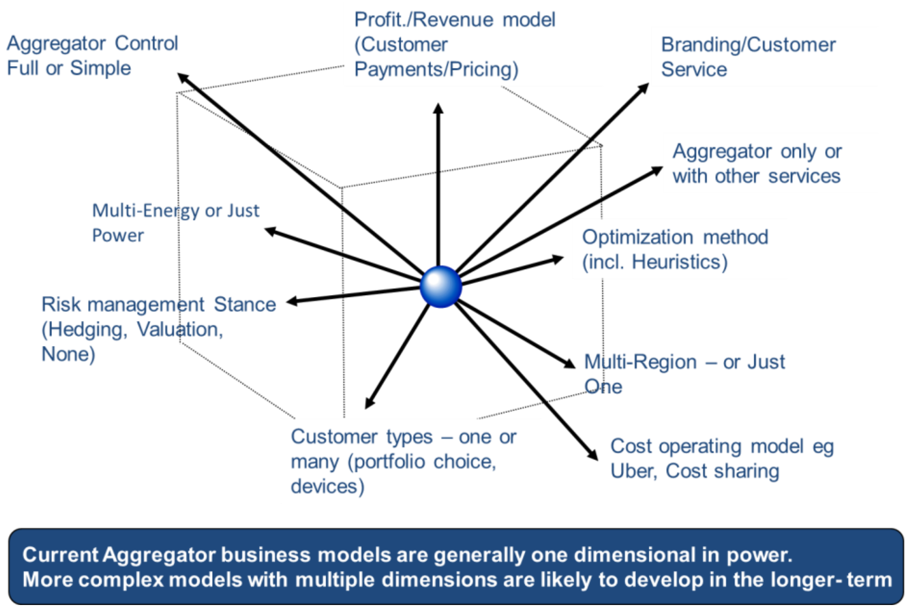

Figure 4-7: Multi-Dimensional business model framework: Power aggregation

The model dimensions include:

- Geography (aggregators may operate across geography – e.g. Amazon and Google would).
- Energy vectors (selling across power, gas and heat sectors – but this thesis will only focus on the power energy vector).
- Whether the “control” of flexibility by the aggregator would be fully automated or by some informal mechanism with penalties for non-delivery.
- Branding and marketing.
- Portfolio or “bucket” optimization algorithms.
- Different revenue generation models (which would include contract types, parameters such as price levels, contract lengths and so on).
- Customer portfolio selection (types, sizes types of flexibility [eg EV only or a

mix]).

- Risk management stance – e.g. fully hedged to minimize downside risks or with no risk management at all.

4.2.4 Evolution of Business Models

All of the papers cited so far, assume business models are stationary and do not consider the evolution of such models.

Arthur Andersen [230] in analyzing emerging gas and electricity business models in what was then the newly emerging competitive gas and electricity markets in Europe, developed a "predictable patterns framework" for discussing potential future developments and approaches. Their framework assumes that market structures (stages) evolve at different speeds along this framework from left to right and use it to compare the evolution of European markets. An adaption of said framework for the aggregator context is shown in Figure 4-8.

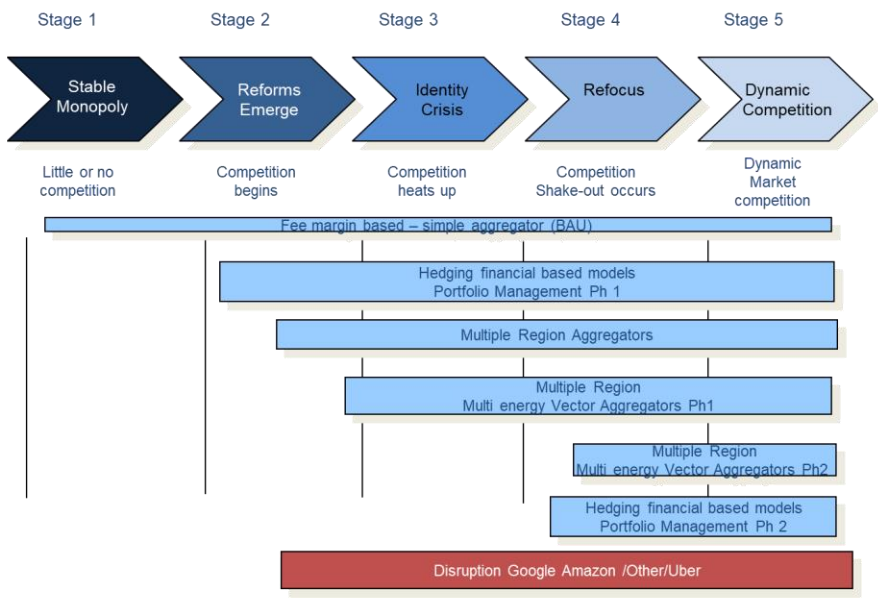

Figure 4-8: Stages of competition: Evolution of business models: Adapted from Arthur Andersen [230] by author

It is widely accepted that development along the horizontal access of this diagram (sequentially left to right) is likely to be incremental for many companies. However, disrupters like Google, Amazon and others will disrupt these markets and potentially leapfrog market stages.

4.2.5 The Disrupters

"People used to laugh at the idea of their businesses falling victim to a online business run by people who had no idea about books" [231] . In the same way, that company in the reference (Amazon) disrupted the book store industry, they are now slowly making strides into the power business and specifically the power demand side response business and eventually the aggregation business. In fact Amazon along with Google, Microsoft and maybe some others have the potential to reshape the power industry by introducing digitally based business models at scale.

"The energy sector has not yet been conquered by a platform giant like Amazon, Spotify or Facebook…But there are reasons why this will happen soon. The only question is, who is going to be there first?" *[232]*

Two important elements of this digital strategy is a brand name and a cost-effective platform with an ability to treat the electricity user as a customer. This would include a digital platform that links the purchasing, trading and management of decentralised generation assets together with the low-cost management of customer demand. Essentially Amazon and Google or even a full blown large trading company has the where with all and the technology potentially to form a business with a digital platform to manage aggregate and trade in the energy sector. They also have the financial might also to buy out existing or newly formed companies in this segment.

Forbes in a similar article [233] cites a number of examples where acquisitions of home automation technology seem to be the first step to forming new electricity energy businesses i.e. Amazon Echo to expand into the electricity business and the customer flexibility business in particular. Alphabet (parent of Google) acquired the Nest home automation device in 2018. [234]

Amazon also invested in a $61 million fund for Ecobee, a Nest competitor (Smart thermostat), in March 2018 [235]. Seven months later, it struck a partnership with Arcadia Power, a home-efficiency bundler with a liking for smart devices. Amazon has also been aggressively building out its Echo platform for connected devices.

BP has recently purchased an EV charging business [236] and Total has invested in Battery Storage [237][81]. Shell and BP have made moves in the US to get into the Electricity retailing business [238]. These companies have great financials, already participate in trading markets with the appropriate software and expertise and could easily enter the aggregation business in the longer term. Tesla has recently announced that it will enter the UK energy retailing business too [239].

4.2.6 Six Business Models on Two Dimensions – Illustrative Case Study

To make this problem more tractable, this thesis is going to focus on two business model dimensions, namely the revenue generation model and risk management stance. *Six business models based on the two dimensions have been created and used in a case study discussed later in the Chapter 8.* Figure 4-9 summarizes the case studies using scheme numbers and Figure 4-10 presents the case study schemes in terms of risk and

[81] Purchases made in 2019/2020.

customer contract/payment method.

		Risk Management Stance	
		No Risk Mangement	Fully Hedged
Revenue Generation Model	Pays Customer a % of cleared price	*1*	*4*
	Pays Customer bid price	*2*	*5*
	Pays Customer a fixed price	*3*	*6*

Figure 4-9: Revenue Vs Risk Stance; Scheme Numbers

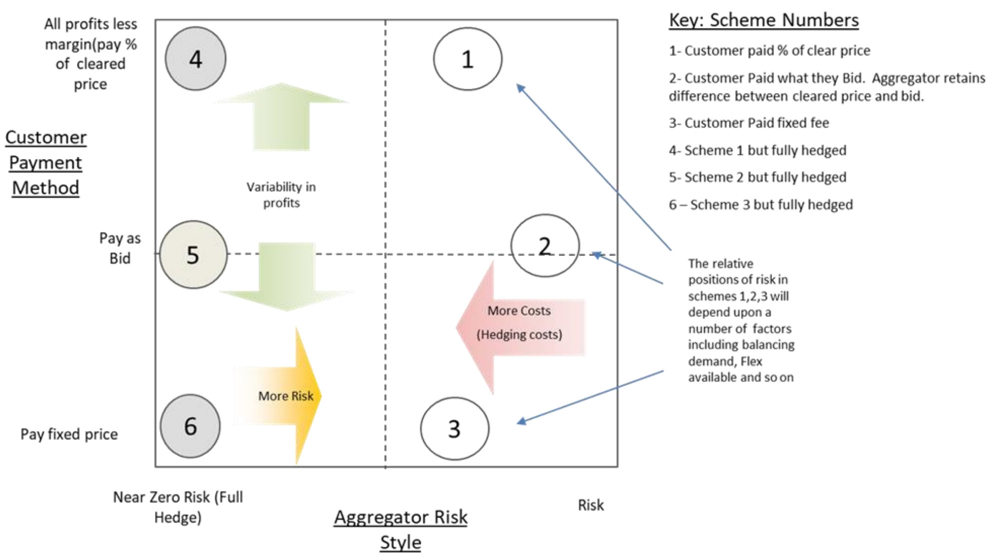

Figure 4-10: Revenue Vs Risk stance; Relative positions of business models

Details on the mechanics of these business model schemes is given in *Table* 4-1. The first three schemes represent the three revenue business models without risk management. Schemes 4-6 include risk management to fully hedge away downside risk (See Chapter 5). Other hybrid or other contractual models could be developed, but the aim here is to use these business models to see how they affect prices in a simulated market and to consider under what circumstances one business model might be better than another.

Scheme Number	**Aggregator Business Revenue Model**	**Comment/Description**
1	Pays Customer a % of cleared price	No risk management (Unhedged); Customer provides bid prices. The aggregator collates the bids into smaller bid bins e.g. 1,000's of bids into 10 price ranges and supplies these to the market operator, so that they can clear the market. The aggregator agrees to pay the customer a % of the final cleared price assuming aggregator bids were accepted.
2	Pays Customer bid price	No risk management (Unhedged); Customer provides bids; aggregator packages bids and submits the packaged bid to market as above. The aggregator may add a premium to the bids; assumed zero here. The aggregator receives the Clearing price and customers receive their bid prices. The difference between the bid prices and the cleared price – represents the aggregator's profit.

Scheme Number	Aggregator Business Revenue Model	Comment/Description
4	Pays Customer bid and purchases insurance (put option) to reduce risk to near zero	Hedged Scheme 1.
5	Pays Customer a % of cleared price and purchases insurance (put option) to reduce risk to near zero	Hedged Scheme 2
6	Pays Customer fixed price and purchases insurance (put option) to reduce risk to near zero	Hedged Scheme 3

Table 4-1: Revenue business models

4.2.7 Description of Revenue Generation Model

In developing business models, Samavi, Yu and Topaloglou [196] use a graphical modelling approach which identifies tasks, actors and goals. Burger and Luke [240] use a similar visual depiction method to look and review business models associated with distributed energy resources, highlighting payments, service provisions and other monetary flows between actors.

Figure 4-11 - Figure 4-13 uses as its inspiration the work in [196, 240] to create a business model diagram of the actors, service and monetary flows between them. It focusses on three revenue generation models. Risk will be dealt with, in the next chapter.

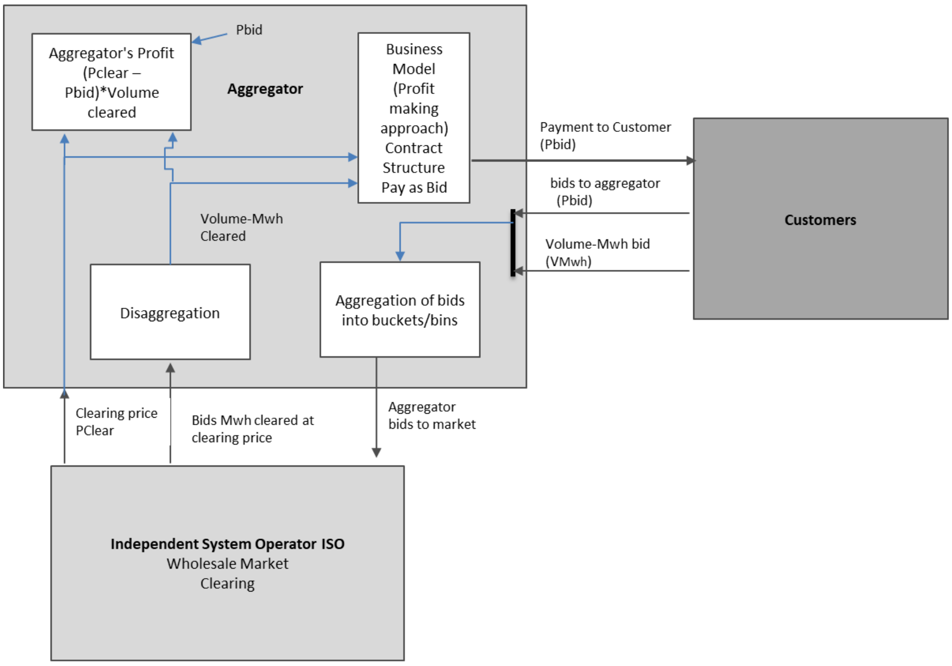

Figure 4-11: Business and revenue generation model: Pay customer as they bid

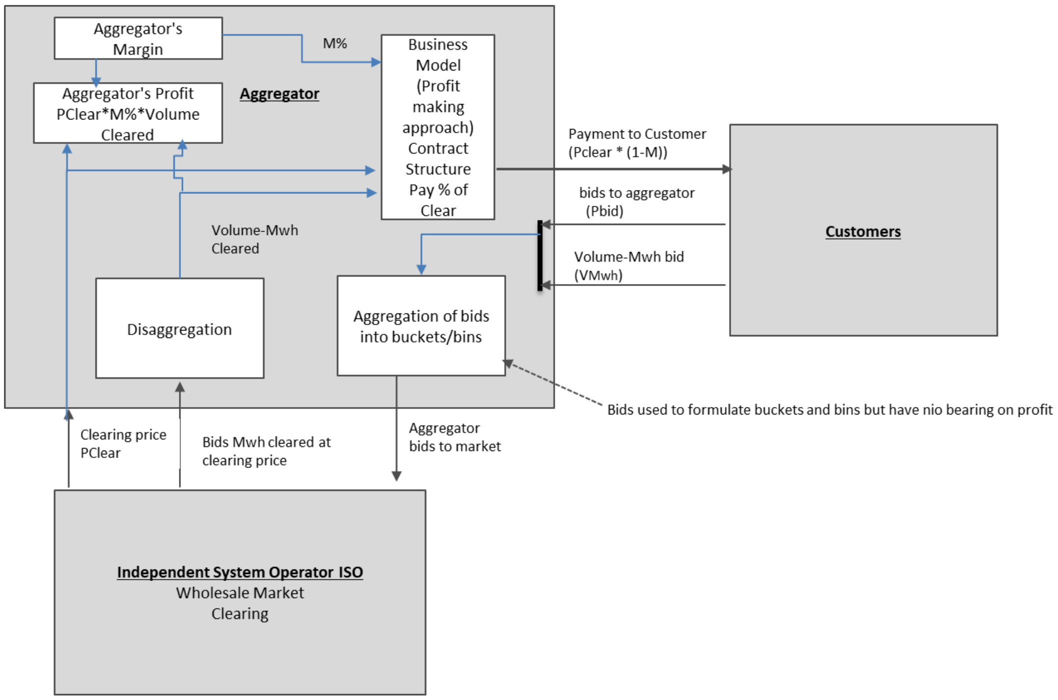

Figure 4-12: Business and revenue generation model: Pay customer % of clearing price

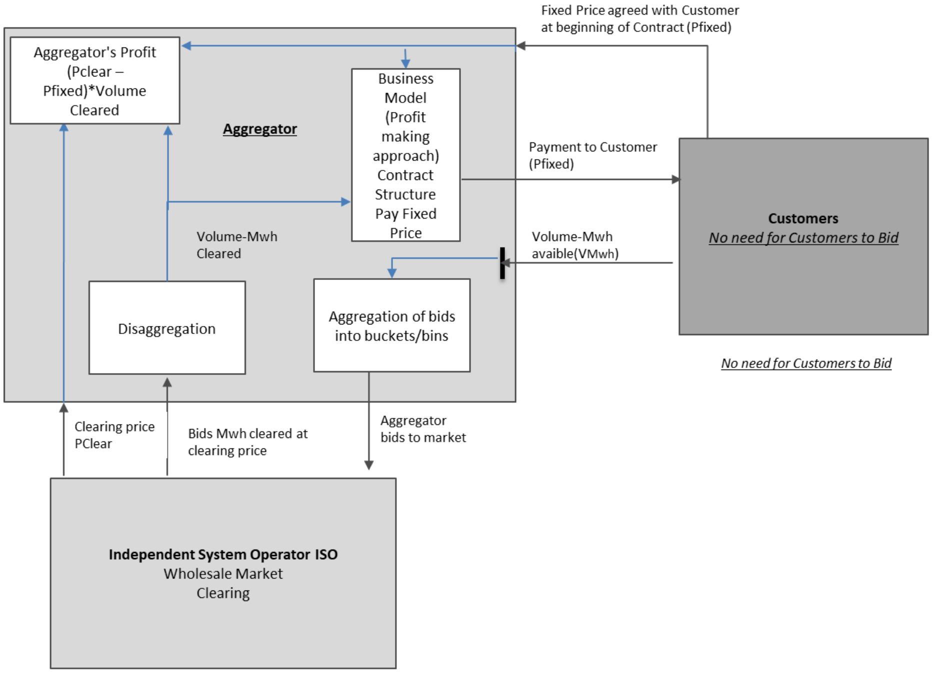

Figure 4-13: Business and revenue generation model: Pay customer a fixed price

Each business model[82] uses a slightly different payment mechanism and defines how the aggregator will generate a profit. Customers bid volumes and prices and they could provide multiple bids e.g. 1 kWh at £20/MWh and 5 kWh at £120/MWh and so on but let us assume just one bid per customer[83]. Customers could also bid both upward and downward flexibility (as per SmartNet see [79, 165]). An analysis of UK balancing volumes indicates that over the period (September 2016 – October 2019) 61% of the flexibility demands have been for upward flexibility[84].

Equations (4-1) – (4-3) below detail profits to the aggregator for each revenue model. This profit is for one time-period – for a bid in the next hour and for 1 bin or bucket only. Bids would only be cleared by the aggregator when the clearing price is greater than the average bid price. In the case of scheme 2 (pay customer as % of clearing price), the aggregator would only submit such bids if the expected revenue from clearing price (P_{clear}* aggregator margin) is greater than the costs it would be expected to incur.

Pay customer Bid $$\Pi = \max[0, (P_{clear} - P_{bid})] * V_{mwh} - C_{opx} - C_{cpx} \quad (4\text{-}1)$$

Pay % Cleared $$\Pi = \max[0, (P_{clear} * \text{margin}_{agg} - P_{bid})] * V_{mwh} - C_{opx} - C_{cpx} \quad (4\text{-}2)$$

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82 No risk management is assumed in these diagrams.

83 Not all customers will want to submit bids in this way and may delegate bidding to an aggregator or some other third party or software application.

84 Data and analysis as discussed in Chapter 2.

Pay fixed $$\Pi = \max[0,(P_{clear} - P_{fixed})] * V_{mwh} - C_{opx} - C_{cpx} \qquad (4\text{-}3)$$

Where:

Π - *Profit (£)*

P_{clear} - Clearing Price in next hour (£/MWh)

P_{bid} - Weighted Average Price bid in bucket[85] – assumes that bid is based on the weighted average but could use a different approach (£/MWh)

V_{mwh} - Cleared Volume associated with bid in MWh. This would be the same as the bid volume if 100% of the bid is accepted

margin_{agg} - % of clearing price that aggregator keeps. Customers would be paid $(1\text{-margin}_{\text{agg}}) * P_{\text{clear}}$

C_{cpx} - Cost associated with Capital costs (CPX) for one time-period

C_{opx} - Cost associated with operating costs (CPX) for one time-period

Hedged positions (schemes 4-6) would include an additional cost associated with the cost of the hedge. As will be shown in section 5.7, this cost can be represented using a put option.

4.3 Economics of the Aggregator

By using the cost model (Section 4.1.5) and the three revenue models discussed above, an analysis of the economic value (Net Present Value – NPV) and profit margins is shown below from an aggregator's point of view. Based on the weighted

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[85] *Assumes that bid is based on the weighted average but could use a different approach.*

average cost of capital (WACOC) and hurdle rates for energy projects that have been investigated in [241-243] and indicate ranges of 7.5 – 14%[86]. A discount rate of 10% has been used here in such assessments of the NPV in the figures below.

UK imbalance prices[87] [76, 244] over the years 2010 to 2020 have been used to construct an average balancing price profile throughout one year and used to calculated hourly revenues. Yearly cashflows[88] have been generated and NPV's, internal rates of return (IRRs) etc. calculated. The model that was constructed for this purpose allows changes in parameters such as number of customers etc. A breakeven analysis using the number of customers is shown in Figure 4-14 - Figure 4-15 for an aggregator with and without industrial/commercial customers[89]. Domestic customers are assumed to have an average yearly load of 4,000 kWh/year (without EV's) and Industrial customers 35,000 kWh/year. Graphs show different curves assuming that only a percentage of this load is flexible[90]. Figure 4-15 shows that if the aggregator has around 1500 - 1600 SME customers then no domestic customers are required for the aggregator to breakeven. The addition of EV's to the base case (assuming 100% EV penetration) would reduce the number of domestic customers (without EV's) required to breakeven by about 50%. EV's are assumed to use 40 kWh per week and negates the need for the higher number of customers.

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[86] There is one example with a rate of 22.7% but is associated with very risky projects.

[87] Elexon data.

[88] Cashflows for each of the next 20 years are assumed to be identical.

[89] This is a simple breakeven analysis looking at revenues = costs.

[90] Note that in Chapter 2, it was suggested that only a maximum of 28% of the domestic load would be available for flexibility.

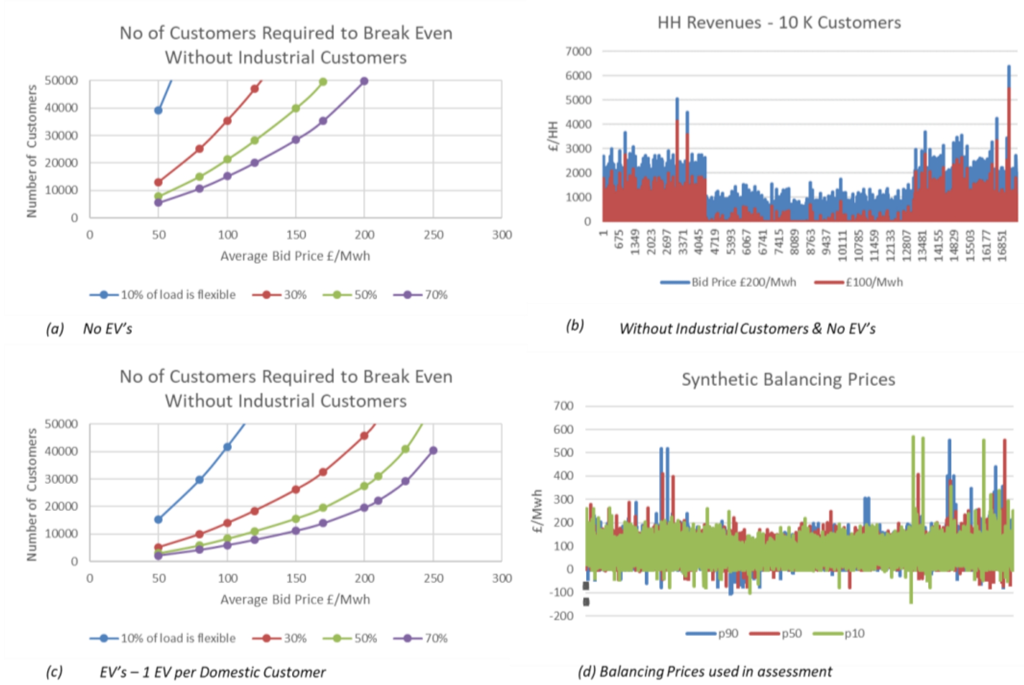

Figure 4-14: Breakeven analysis of aggregator business; No industrial customers

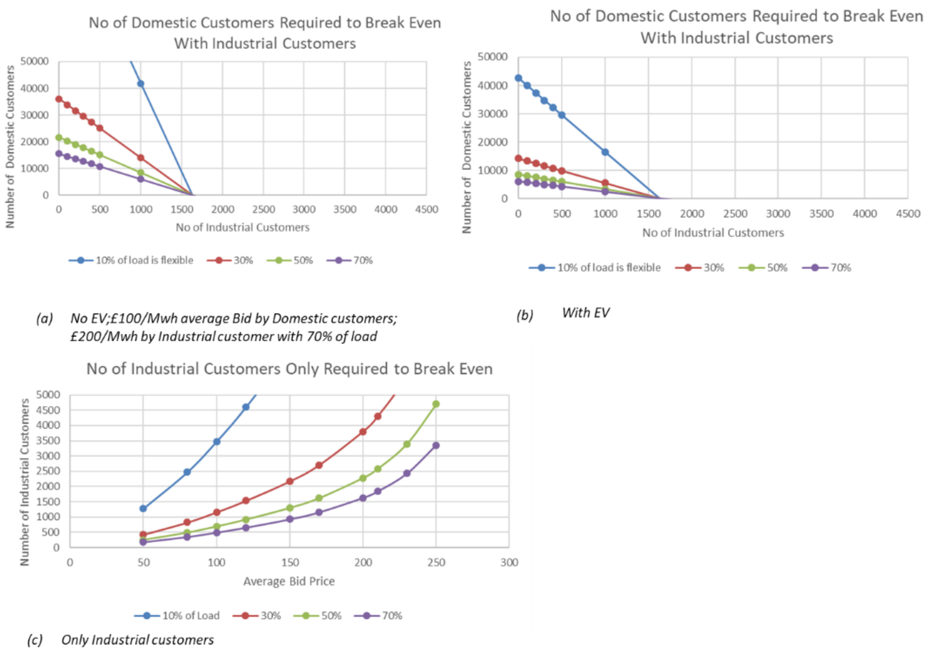

Figure 4-15: Economics of aggregator business; The effect of industrial customers

The city of Dundee in Scotland currently has around 4500 SME business in the area of interest under study in later chapters. If six aggregators equally acquired the same number of Industrial customers, (i.e. 750 each) they will need around 10,000 domestic customers to breakeven (with EV case)[91].

4.3.1 Unit Breakeven Prices

Market clearing prices will need to cover the costs of running the aggregator business. Figure 4-16 shows the clearing or breakeven price that would be required just to cover annualized capital and operating costs[92] both on marginal and full cost basis. Note that capital costs have been depreciated on a straight-line basis over 10 years and used to estimate full costs.

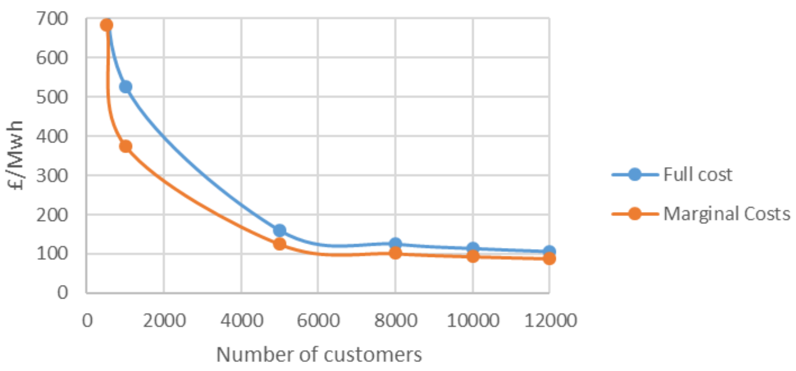

Figure 4-16: Aggregator Unit Costs £/MWh

Average UK balancing prices prior to 2020 were around £200/MWh, so balancing prices could cover operating and capital costs[93], assuming aggregators could attract circa 10,000 domestic customers alone. This would allow bids up to £100/MWh to

[91] Assumes customer bid price of £100/MWh. This would also be balancing volume dependent.

[92] Annualised Capital costs are calculated assuming a discount rate of 10%.

[93] OPX and CPX costs equates to around £100-120/MWh for 10,000 domestic customers.

occur from customers (on average).[94]

4.3.2 Aggregator Economics: NPV's and IRR's

The economics of an investment in an aggregator business can be evaluated using discounted cashflows using standard measures like Net Present Value(NPV) and Internal Rate of Return (IRR) (see Brearly and Myers ch 2-6 in [81]). NPV, discounts future cashflows at a discount rate dependent upon the weighted average cost of capital (WACOC) of the business. This can be calculated using the CAPM model discussed in section 5.9.3[95] with methods highlighted in [81, 245]. Yearly cashflows and NPV's can be estimated by using the following equations. These assume the Pay customer bid business model (equation (4-1), but can be extended for the other revenue model cases. Note equations associated with Domestic Customers and EV volumes have been excluded for brevity but essentially follow the format of equation (4-4), except that volumes and percentages would be for that for the appropriate variable.

$$VolumeIndustrial_i = (\%loadflexibleInd * AverageIndHourlyLoad * \%availforflexInd) * N_{ind} \tag{4-4}$$

$$Volume_i = VolumeDomestic_i + VolumeIndustrial_i + Volume\_EV_i \tag{4-5}$$

$$\mathrm{Re}v_i = (Pclear_i - Pbid) * Volume_i \quad for\ all\ Pclear_i > Pbid \tag{4-6}$$

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[94] This ignores any costs for risk management or to cover profit margin requirements.

[95] Capital Asset Pricing Model (CAPM) answers the question how is risk related to returns.

$$\mathrm{Re}vs_{yr} = \sum_{i=1}^{8760} \mathrm{Re}vs_i \qquad (4\text{-}7)$$

$$CF_j = (\mathrm{Re}vs_{yr} - OPX - CPX) * (1 - tax\_rate) \qquad (4\text{-}8)$$

$$NPV = \frac{CF_j}{(1+r)^1} + \frac{CF_{j+1}}{(1+r)^2} + \dots \frac{CF_{j=n}}{(1+r)^n} \qquad (4\text{-}9)$$

where:

$VolumeDomestic_i$ – Domestic Flexibility MWh for the i^th hour
$VolumeIndustrial_i$ – *Industrial* Flexibility MWh for the i^th hour
$Volume\_EV_i$ – EV Flexibility MWh for the i^th hour
AverageIndHourlyLoad – Total Hourly load MWh -Industrial
%loadflexibleInd - % of Hourly load that is flexible - Industrial
%availforflexInd - % of flexible load avail for use in market - Industrial
$Revs_i$ - Revenue for the i^th hour
$Pclear_i$ – UK balancing price in i^th hour
$Pbid$ - Average price bid - assumed £70/MWh for base case
$RevYr$ – Revenues over year
CF_j – Cashflow in j^th year
OPX – yearly OPX – assuming constant real OPX
CPX - initial investment in year 0 - – assuming constant real CPX
Tax_rate – corporate tax rate – assumed to be 20%
r – discount rate
$Ndom$ – number of domestic customers
$NInd$ – number of Industrial customers (SME's)
$NumberofCars$ – average number of EV's per household
$PenetrationEV$ – Penetration of EV cars in market 0-100%

Summary statistics for the pay as bid revenue model for three cases (using the equations above) are given in Table 4-2.

Description	**NPV £ millions (Real 2020) @ 10%**	**IRR (Real 2020) %**	**NPV/I**	**Payback Years[96]**
<u>Base Case</u>: 10,000 Domestic customers, No Industrial customers, No EV's	-£2.01	N/A	-1.76	No payback
10,000 Domestic customers, No Industrial customers, 100% penetration of EV's	£8.4	47%	7.32	2.14
10,000 Domestic customers, 750 SME Industrial customers, No EV	4.3	26%	3.81	3.76

Table 4-2: Aggregator economics summary (NPV;IRR; NPV/I and payback years)

An NPV and IRR sensitivity analysis against the base case is shown in Figure 4-17 and Figure 4-18. NPVs for key parameters are shown with percentage changes in the base case parameter assumptions. Parameters are varied ceteris paribus.

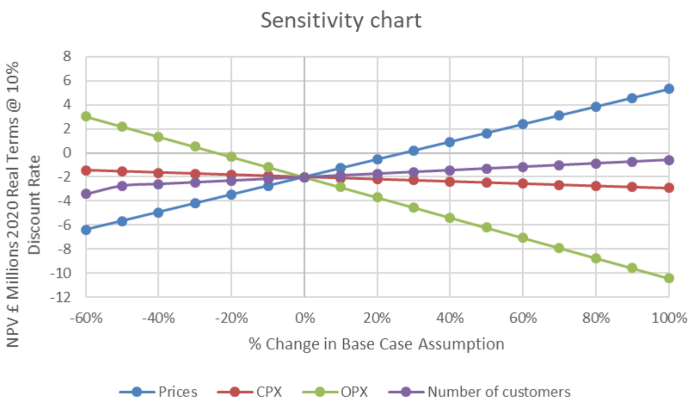

Figure 4-17: NPV Sensitivity chart for an Aggregator Business; No EV

96 Simple Payback – when cumulative revenues cover cumulative costs

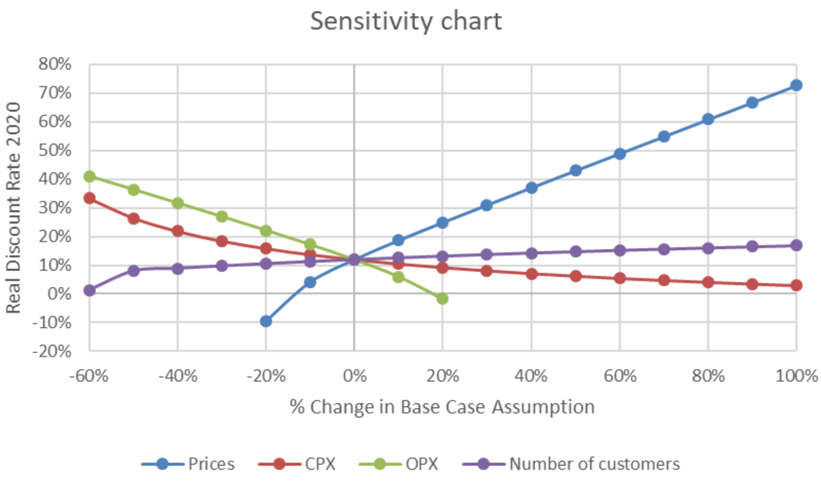

Figure 4-18 Real IRR% Sensitivity chart for an Aggregator Business; No EV

A comparison of various scenarios against the base case described above, is also shown in Figure 4-19. Each scenario changes one or two aspects of the base case assumptions, whilst keeping others constant.

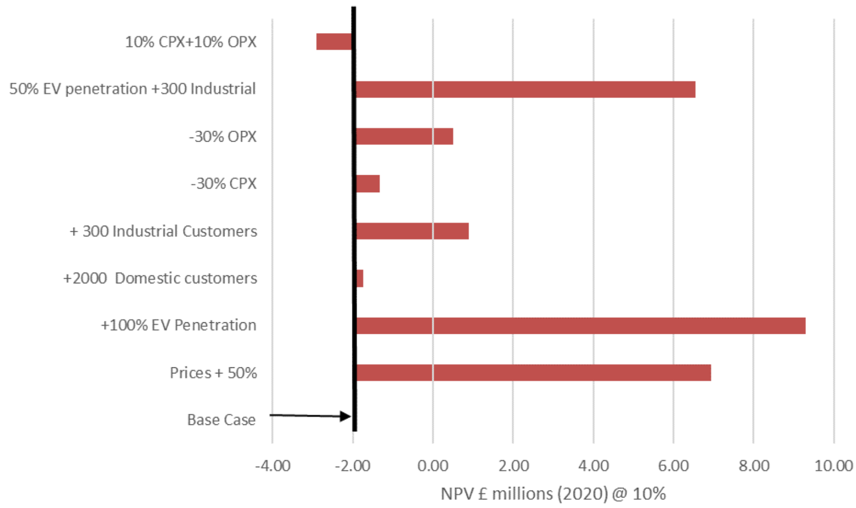

Figure 4-19: NPV sensitivities

Payback periods[97] for the base case never pay back and for the scenario where

[97] Simple Payback - Cumulative cashflows = CPX. No discounting.

prices in the base case are raised by 50% - 7.1 years. With 100% penetration of EV's, payback periods drop to 1.8 years. A no EV case with 1500 industrial customers in addition to the 10,000 domestic customers drops to 1.35 years.

Key Points: Economic Analysis

- Need around 10,000 domestic customers (without industrial customers) to breakeven (with the assumptions adopted here).
- EV's would be key to improving aggregator economics.
- Acquisition of Industrial customers is also key to the profitability of the Aggregator business – but competition for these customers could be fierce.
- This analysis does not account for risk.

4.4 Chapter Summary

Although literature has reviewed the current business models in power aggregation, little work has been performed on more sophisticated models likely to be used by commercial aggregators in the future including modelling of risk. Neither is there any detailed cost or economic literature. This has necessitated the need to formulate future business models, views on the costs, and revenue generation models, so that the economics and profitability of an aggregator could be investigated and is a contribution to the state of the art. This forms the basis of the ABM modelling of commercial aggregators discussed later in the thesis. In addition, the revenue models that have been developed in this section will be used to evaluate the risk associated with aggregators in Chapter 5.

Chapter 5

Risk Management in Power Aggregation

5.1 Introduction

This chapter provides background information on risk management, in the context of a commercial aggregator in the power domain. Risk management consists of valuation and risk control. Risk valuation methods are overviewed, but this thesis focuses on the use of put options as a method to quantify risk in a power aggregator interacting with domestic customers. In the context of this, option theory and the use real options in power aggregation is reviewed. There has been extensive use of real options in the valuation of contracts in the power domain, but there are no papers that currently analyze aggregation using this framework. This is not surprising as aggregation is a relatively new concept in the domain. The paper uses a three asset put option framework to value risk and later uses this as a basis to manage such risk. Put options can be viewed as insurance premiums, which can be purchased in a theoretical market to manage downside risk and are later used in Chapter 7 and 8 to value and represent risk within an aggregator agent in a simulation. The risk associated with the business models introduced in section 4.2.6 are valued. Finally, financial portfolio management concepts are introduced and are used to help select amongst these various business models. This Chapter makes extensive use of the concepts used in financial options, while omitting introductory material that can be found in literature, e.g. a good introductory text is [81] (chapters on options and risk management). The structure of the chapter is summarized in Figure 5-1 below.

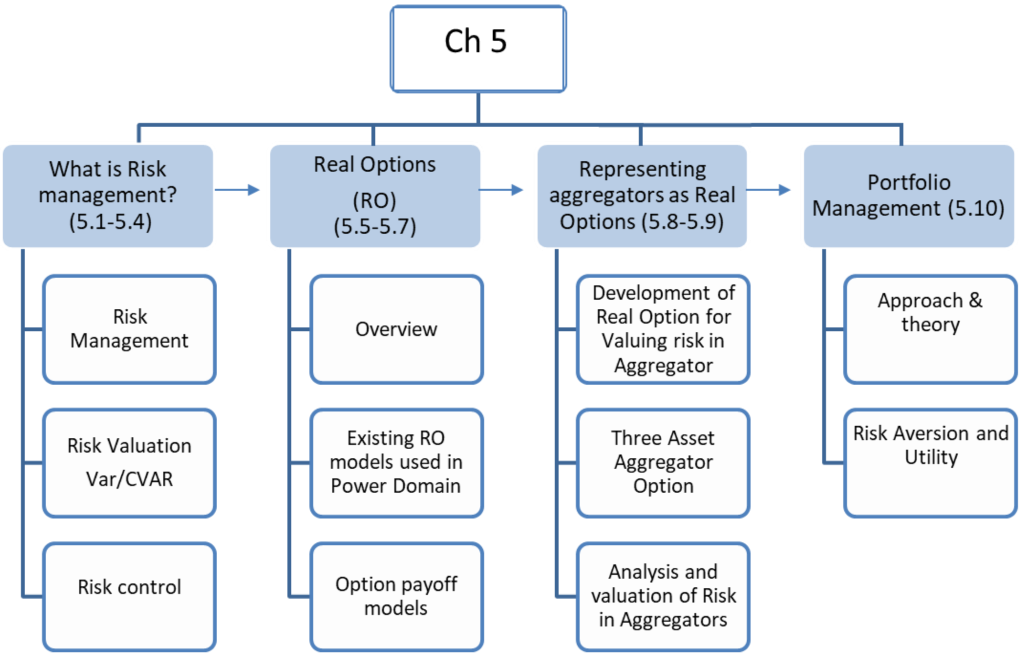

Figure 5-1: Chapter 5 overview

5.2 Risk Management

It is well known in the business world that higher profits are associated with higher risks (see Capital Asset Pricing model (CAPM) discussion later section 5.9.3). Adequately quantifying and mitigating those risks is therefore an important part of running a corporate enterprise and risk management is an important process used to manage these risks. The process involves identifying and analyzing the amount of risk involved in an investment, such as that being made by a commercial power aggregator, and either accepting that risk or mitigating it. Hedging is a typical approach used in mitigation. Risk limits[98] may also be applied to limit the risk involved in a portfolio position. Some common measures of risk include standard deviation, value at risk (VaR) and conditional value at risk (CVaR).

Pilipovic ch9 [246] defines risk management as " the process of achieving the desired balance of risk and return through a particular trading strategy. The risk return framework incorporates the full business process of selecting, communicating, valuing and achieving this balance within the firms portfolio of assets … Valuation focusses on the price of the individual contracts; risk management focuses on the change in price, both on an individual contract basis and on a portfolio wide basis"

There are therefore two parts to risk management – to value the risk and then to manage it.

5.3 Risk Valuation Overview

Risk can be valued using statistical techniques or financial theory like options. There a number of methods to value risk including:

- **Risk adjusted Prices[99]** (including put option approaches)
- VaR (Value at Risk)
- CVaR (Conditional Value at Risk)

---

[98] "A Risk Limit is a general and widely used risk and portfolio management technique. It denotes one or more numerical thresholds defined in relation with specific risk exposures such as Credit Risk, Market Risk or Liquidity Risk exposures. [https://www.openriskmanual.org/wiki/Risk_Limit]. Only Market Risk is considered in this thesis.

[99] The risk adjusted price is the method used in the simulations in this thesis. Others given for completeness.

These are summarized in Figure 5-2.

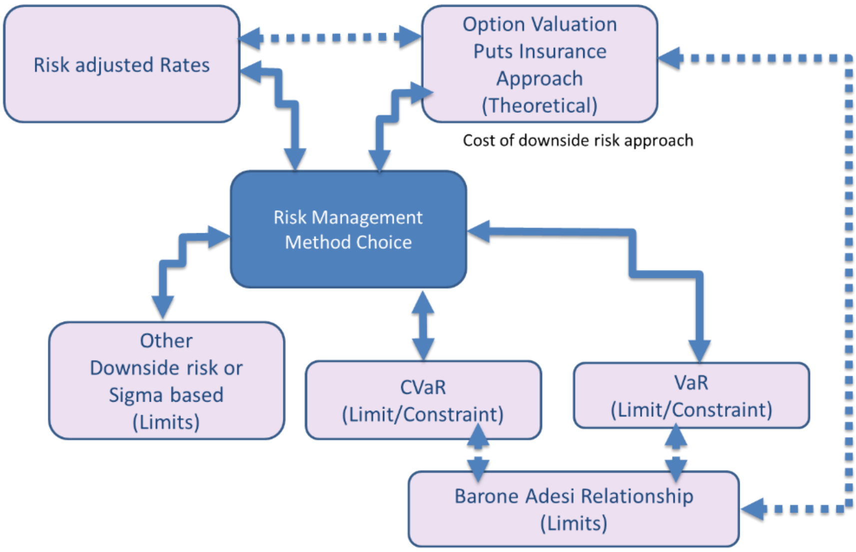

Figure 5-2: Risk management valuation approach

5.3.1 Value at Risk (VaR)

Jorian [247] defines VaR, as the maximum expected potential loss on the portfolio over the given time horizon for a given confidence interval under normal market conditions. In other words, there are three key elements to describe the Value at Risk (VaR): (i) the time period; (ii) the potential loss from the portfolio and (iii) a confidence interval e.g. 95%.

RiskMetrics [248] define Value at Risk (VaR) as a statistical measure used to assess the level of risk associated with a portfolio or company. VaR measures the maximum potential loss with a degree of confidence for a specified period. For example, suppose a portfolio of investments has a one-year 95% VaR of £10 million.

Therefore, the portfolio has a 5% percent chance of losing more than £10 million over a one-year period.

VaR can be calculated using three methods:

- Delta Normal approximation
- Historical simulation
- and Monte-Carlo

The Delta Normal VaR method is the simplest and is extensively used in Industry, in systems like RiskMetrics and by market exchanges on millions of assets. It assumes that distributions are normally distributed for all risk factors, e.g. price, and that assets are linear in those risk factors. Options are linearized using option deltas. The key concept in the Delta Normal method is Value at risk or VaR and is calculated using the portfolio delta.

VaR is simply calculated using the following formula for d days:

$$V_{VaR} = 1.96\,\sigma\,\Delta\,V\,d^{0.5} \tag{5-1}$$

where:

V_{VaR} - *Value at Risk*

σ - Volatility or Standard Deviation for 1 day eg 1% [100]

d - Number of days

Δ – Option/Futures portfolio Delta

[100] The σ for different time periods is related by the square root of the time - see Hull. [249].

V – Value of instrument e.g. future or option

Note 1.96 is the Z score associated with a confidence limit of 95%.

When assets are independent and equally weighted, portfolio VaR can be calculated by summing the squares of the individual VaRs and taking the square root. Correlation amongst assets would need a calculation talking account of the covariance between pairs of assets. The Delta Normal method is therefore the simplest technique to implement as the portfolio return is a linear combination of normal variables of the individual assets.

Historical simulation is also relatively simple to implement and uses historical price patterns to simulate future outcomes [246] (p 192-193). The procedure for calculating VaR using historical simulation is outlined in [250]. In summary it uses historical returns /profits. Returns are sorted in order to produce a probabilistic view of actual returns and profits. Of course, historical price patterns may not reflect the future.

Monte-Carlo simulation of VaR allows for simulation that includes any interactions between assets. It also includes all possible future price paths in its calculation and is the most accurate method [246] (p 191-192) for assessing VaR. It can incorporate non-normal distributions, sophisticated correlations between assets and can apply different pricing models. The downside is that this can be computationally inefficient.

5.3.2 Conditional Value-at-Risk (CVaR)

Conditional Value-at-Risk (CVaR) was introduced by Rockafellar and Uryasev in [251], and is a risk measure used to assess the tail risk of an investment. It is also known as expected shortfall or exposure risk. Used as an extension to the VaR, CvaR integrates the distribution above the VaR value to obtain what is essentially a weighted average loss[101]. This measure is more sensitive to events that happen in the tail end of a distribution.

For the interested reader, Uryasev reviews the uses of and pros and cons of each of CVAR and VaR [252]. CVaR has become a popular risk management method due to its relation to VaR, and it is an informative risk measure and deals with the issues of large losses associated with fat or long tail distributions.

Errors in the use of VaR becomes more significant when commodities have heavy or long-tailed price distributions, and exhibit a high potential for large losses [253]. These long tail distributions could be exhibited in the clearing prices modelled with aggregators. This would occur when system failure events cause prices to rise.

5.3.3 Risk Adjusted Prices: Put options

"The most common way of adjusting for risk is to compute a value that is risk adjusted." [245]. This is what Banks do when they assess credit or lending risk. They increase interest rates to less credit worthy customers. Damodaran [245] considers four ways in which this risk adjustment can be made. The first two approaches are based upon discounted cash flow valuation, where the discount rate is adjusted for risk. The fourth approach, adjusts for risk by observing market premium for similar assets. The third approach, the one this thesis uses, is a post-valuation adjustment; a discount for potential downside risk. A put option can be used to value this downside risk. The owner of a put option has the right to sell its goods, in this case flexibility volumes

[101] Effectively losses multiplied by probability in the tail of the distribution.

(MWh), at a price P and will always receive at a minimum, a value known as the strike price K. A Contract for Difference (CFD) payment [254] is actually a put option. For example, a wind farm owner will always receive the strike price e.g. £150/MWh even if the market price is £50/MWh. If market prices are higher the provider of flexibility would receive the higher price.

The seller of the flexibility option would seek a payment for this option right – known as an option premium[102]. The finance discipline has developed pricing formulas that estimate the value of this premium, depending on the prices (P and K), the volatility in prices and the time to expiry of the option.

Engineering and business consulting companies that provide proposal bids use the risk adjusted approach in an unsophisticated way. Contingencies set at 10-15% would typically be added to cost estimate to cover for risk.

Brearly and Myers (Ch11) [81] introduce the idea of using a put option to insure against the downside risky company cashflows. The example in [81] considers a company with uncertain cashflows, but the owners want to make sure that they always earn a certain level of cashflow – set by a threshold level. If one were available, it would be possible to buy a put option to insure against the cashflow downside. When cashflows are below the threshold, the put option would payout the difference between the threshold and the actual outturn cashflow. If cashflows are above the threshold, the put option is worthless, as nothing would be paid out. The company wishes to do this monthly so the company buys a strip of options, one for each month, with the

[102] Note Governments may not ask for a premium as in the case of a CFD.

options expiring in month one, month two and so on. Option theory can be used (see Brearly and Myers CH11 and Ch 20 [81]) to value this option and would be equivalent to what a company would have to pay for this insurance. It therefore represents downside risk in "one number" taking account of uncertainties in key variables. Damoradoran [245] also introduces the idea of using a put option to value risk and to adjust NPV's. In a similar way Ang, Chen and Sundaresan [255] use a put option to characterise the downside risk in pension fund portfolio selection. Pension funds have liabilities to their current and future pensioners that must be met so a put option approach that includes these liabilities is an approach that values the portfolio by considering the downside risk. The liabilities or threshold are the exercise price in this put option.

5.4 Risk Control/Mitigation Overview

The various measures discussed above are important inputs in any risk control strategy to be used. Market/exchange based options and futures can be bought to reduce or manage risk to an appropriate level. The European markets currently have 10 power future contracts and only 3 power based options available. The USA has 165 and 16 respectively.[103] This somewhat limits what risk managers can do to curtail risk. Other options from similar markets could be used, but would result in other types of risk[104]. Development of future options and futures markets, especially in Europe, maybe essential if aggregators are to fully manage the risk inherent in a power

[103] Obtained by inspecting the ICE and CME websites for power contracts (futures and options).

[104] For example basis risk. Basis risk refers to the risk that an exchange contract will not perfectly cover the underlying position.

aggregation market. Risk control can be categorized into Dynamic and Static hedging and is summarized in Figure 5-3 below.

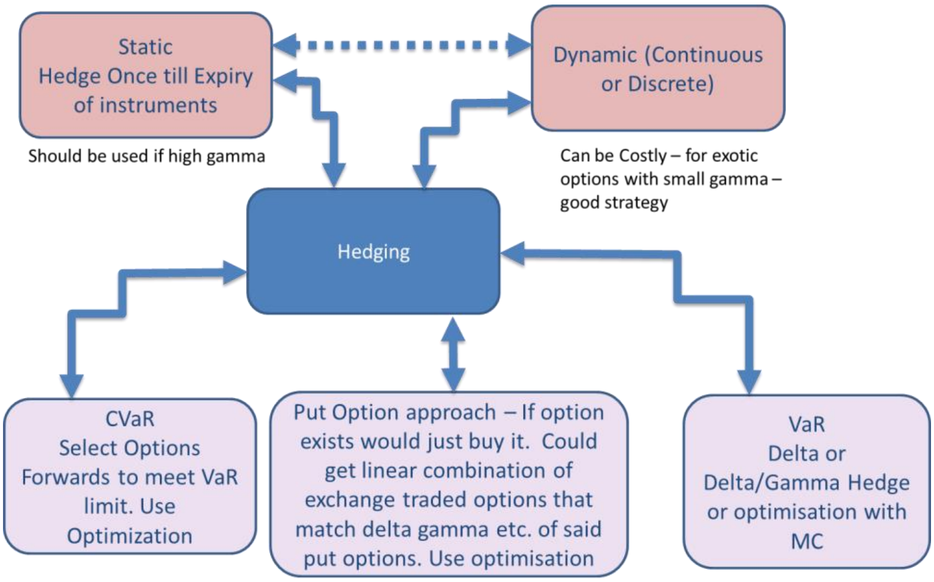

Figure 5-3: Risk control approaches (hedging)

The static hedging approach uses a portfolio of standard exchange traded options and futures, and this portfolio is maintained either until the expiration of the portfolio of options or until some other event. Rebalancing of the portfolio does not occur between these times. In the dynamic hedging, portfolios are continuously re-hedged. At the extreme, balancing could be performed continuously. Of course, once transaction costs are accounted for, this could become very costly. A side calculation by the thesis' author on the cost of continuous hedging vs a discrete time approach e.g. re-hedge/rebalance every Y days rather than every hour – shows that in the case of aggregator using Delta hedging, that costs and hedging error ([256] Ch 20) would be minimized using a discrete hedging approach approximately every 10 days. Of course, this depends upon market conditions and other assumptions.

Zhang [257] shows that static hedging is better for options with high gamma[105] and discrete hedging is better for options with small gamma. Static versus Dynamic Hedging of Exotic Options was also evaluated by Tompkins for many different types including correlated exotic options [258] [106] and found that " Neither dynamic nor static hedging approaches were found to be universally superior. For many exotic options, the dynamic hedging approach performed as well as, or better than," the static approach.

5.4.1 Delta and Delta Vega Hedging

The option Greeks can be used to calculate the sensitivity of the options to price and volatility movements, and therefore can be used to hedge, assuming price movements are relatively small (see [249, 256, 259, 260] for discussion of hedging with Greeks). Option Greeks are used to provide an estimate of how option value will react to a given change in some of the variable pricing inputs. That is, the underlying asset price (e.g. clearing price), volatility, time to expiry and so on. It is therefore a form of sensitivity analysis. The most commonly used Greeks[107] are Delta (change to price), Gamma (change in Delta), and Vega (change in volatility). The Greeks used in this work are shown in algebraic form in equations (5-2) - (5-4) below.

---

[105] 2nd derivative on price – change in delta with price.

[106] It will be shown later, that the aggregator portfolios consist of correlated exotic options.

[107] Sometimes Theta (change in time to expiry) and Rho (change in risk free interest rate) might be used.

$$\Delta = \frac{\mathrm{d}V}{\mathrm{d}P} \tag{5-2}$$

$$\gamma = \frac{\mathrm{d}V}{\mathrm{d}\Delta} = \frac{d^2V}{\mathrm{d}P^2} \tag{5-3}$$

$$\nu = \frac{\mathrm{d}V}{\mathrm{d}\sigma} \tag{5-4}$$

where:

Δ - Delta

γ – Gamma

ν - Vega

V – Option Value,

P – Underlying Price ,

σ - Volatility

Delta one of the Greeks is defined as the change in value of the option or portfolio for a small movement in the underlying asset e.g. price. Options have a delta ranging from [-1,1]. Futures have a delta of one i.e. a price movement of £1 would result in a future's value movement of one. For interested readers [261] provides a good overview of how one would optimize a portfolio to manage Delta Gamma and Vega risk.

5.4.2 CVaR/VaR Hedging

Portfolio management of VaR/CVaR is achieved via optimization [251, 262]. Typically, Monte-Carlo simulation is used when the portfolio contains nonlinear instruments such as options. The resulting Monte-Carlo distribution of outcomes is used to calculate CVaR and VaR. Unfortunately, this is very computationally inefficient and therefore a normal option delta approximation is often used to calculate VaR. In spite of its drawbacks, the delta-normal approach is widely used among risk managers. For example, the JP Morgan RiskMetrics [248] system is based on the delta-normal model and deals with millions of stocks and assets. The exchange clearing houses e.g. ICE [263], Nymex [264] use a form of normal delta hedging to assess clearing risk and use this to set margin levels in the exchange.

It appears from the literature review on optimal hedging in power that many of the recent papers have focused on CVaR as a methodology, but in practice, many industrial players use other methods. Eon, a large German based power company operating in the UK, uses Delta Hedging to manage its portfolio [265]. In a recent paper Klemola [266] uses a dynamic and static delta hedging strategy in assessing the performance of options in the Nordic electricity market.

Risk management is often conducted in isolation from option modelling, as there has been, until recently, no relation between the two areas. However, the relationship between CVaR and option prices with a closed form solution is detailed in [267]. Barone and Adesi also detail the relationship between CvaR, VaR and a put option (see equation 13 and 14 in [268]), so it is possible under certain assumptions to estimate CVaR directly from put option values. This is important in the context of the modelling that is presented later in this chapter as an aggregator could effectively consist of non-linear options or their equivalents (see later section 5.7 and 5.8)

Although it is a long-term aim to model different types of hedging processes within a company agent, e.g. using CVaR and VaR methodologies and delta hedging, this thesis will focus on the theoretical use of purchasing a real option based on the aggregators downside risk and as described below in section 5.8. By purchasing such an option, risk can be hedged, so that risk is reduced to near zero. The option value also represents a value of risk in one number.

5.5 Real Options

Hull [249], Quail [269], and Wilmott [256, 259, 270] provide a good general introduction to options, futures and other derivative concepts, many of which will be used in the following sections. Clewlow and Strickland [271] set out methods for building models of such derivatives. Mun [272], Copeland and Antikarov [273] provides a good introduction into the use of real option valuation and the assumptions associated with their use.

The term “real options” was coined by Stewart Myers in 1977 [274], referring to “the application of option pricing theory to the valuation of non-financial or “real” investments with learning and flexibility, such as multi-stage R&D, modular manufacturing plant expansion and the like”.

“Real options are not financial options; real options represent certain types of management decisions. The options models used to value real options are borrowed from financial options pricing techniques, but the underlying assumptions of these financial models do not strictly apply to real options…The underlying assets for real options do not normally trade on financial exchanges where market prices are observable. The assets underlying real options are illiquid and hard to trade. If they are being traded, they are usually being bought and sold in inefficient markets, such as in one-on-one negotiated transactions between companies or individuals, not on regulated market exchanges" (Appendix 7.1 in [275]). The assets are usually tangible but can be intangible.

The concept of real options is thus based on the concept of financial options; thus, fundamental knowledge of financial options is crucial to understanding real options. Options are widely used in the trading and the financial industries, but the concepts behind the mathematics of the many types of options[108] can be applied to real assets, by swapping the concept of commodity or stock price with a variable linked to the asset e.g. cashflow or market clearing prices[109]. Essentially, they use the mathematical framework of options to value real life assets like operational flexibility in a power plant.

Table 2 in [276] sets out the differences between financial options and real options. As will be seen some aspects of our valuation are more like financial options and others like real options.

Although real options have been primarily used to look at decisions associated with investments e.g. option to delay investments, expansions, divestments and so on, Ofgem [277] sets out an approach for using real options on gas network interruptible contracts. The document also lists other examples of real option use in the energy industry.

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[108] Including Standard or vanilla options, spark spread options, product options binary barrier options, Asian options (path dependent options) and so on.

[109] Later it will be shown that the option of interest in this thesis uses clearing prices (a commodity), average bid prices and flexibility volumes MWh.

5.6 Representing Power Problems as Options: Real Options and Contracts as Options

Stochastic modelling and use of the more standard types of options in the power industry e.g. the use of spread options in energy contracts and hedging is set out in chapter 9 [278]. Pilipovic [246] also provides a good introduction to the use of derivatives (options) in the energy industry and uses a good number of power industry examples. Deng and Oren [279] review a number of different types of electricity financial instruments and the general methodology for utilizing and pricing such instruments. They also highlight the roles of these electricity derivatives in mitigating market risks for generators, load serving entities, and power marketers.

Ceseña, Mutale, and Rivas-Dávalos [280] review the use of real options in their paper on electrical generation projects especially renewable generation.

Gahungu and Smeers [281] look at capacity expansion on generation assets and technologies and Csapi [282] reviews the use of real options in the electrical power sector using a binomial tree valuation on different generation technologies. In a recent paper Moriarty and J. Palczewski [283] consider operating reserve contracts for battery storage devices using an options framework.

Gardner and Zhuang [284] used a real option approach to value a CCGT power plant to account for the flexibility in its operation including ramp up, minimum and maximum generation levels. Most importantly, their approach not only takes account of market prices but the current operating state of the plant. In this instance, it is a path dependent option that uses a numerical approach to solve the option for operational flexibility.

Liu, M. Zhang, and Z. Zhao [285] in a recent paper reviewed work on real options in the renewable sector and provides references to other papers mainly dealing with investments, their optimal timing, capacity decisions and wind tariffs.

Safarov and Atkinson use a real option approach coupled with copulas (see [286] for an introduction to copulas) and regime switching to optimize and value a natural gas-fired power plant [287].

The majority of the power based real option literature focusses on investment and operational decisions, but some literature focus on contract structures. This literature is now reviewed.

5.6.1 Contract Valuations Using Real options

In the work by de Moraes, Marreco and Carpio [288] real options are used to value the payment that should be received by generators providing flexibility to the Brazilian power market. Similarly, the Italian and Irish power grids are currently considering the use of reliability options. (see [289, 290] for a description of the concept of the reliability option). Capacity providers give up peak prices in exchange for an upfront fee (option premium). Reliability options form a contract between capacity providers and customers, with the sellers of reliability options benefiting from an upfront payment while the buyers benefit from security of supply and reduced exposure to price spikes. Each time the reference price rises above the contract strike price, the seller pays the buyer for the difference. Essentially these are call options (real options).

Swing options or flexibility of delivery options have been valued using an option frameworks by a number of frameworks [291-295]. A swing contract entitles the owner of the contract to exercise up to N times and is typically used by investors who want to buy a predetermined quantity of energy at a predetermined price while retaining a certain degree of flexibility in the amount purchased and the price paid. Jaillet, Ronn and Tompaidis [291] uses a multi-level/dimensional tree or forest approach to value what are a set of complex interactions and decisions over time. The trinomial tree approach [296], first developed by Hull has also been used in the gas industry to value gas storage [297]. A Monte-Carlo approach has also be used to value swing contracts [298] as well as for storage valuation [299].

Although the real option and contract option approaches above provide useful insights into the use of option theory in the power domain, none of the examples is directly relevant to the research questions posed. The representation of Interruptible contracts is somewhat similar to the problem in this thesis, but our domain problem of aggregation is not applicable to these formulations. There are however, some useful lessons that can be drawn for the analysis of interruptible contracts using an option approach.[110].

For example, Kamat and Oren [300] use exotic options (a forward contract with exotic calls at two different strike prices) to mimic an interruptible contract. As they state, the approach allows them to both hedge and value the supply curtailment risk. It assumes that the contract can only be interrupted once and does not consider its effect on spot prices.

Baldick, S. Kolos, and S. Tompaidis [301] extends the work of Kamat and Oren

[110] Much of this work was carried out between 1999 – 2005, but is still relevant.

and includes multiple interruptions, and interactions with spot price. Finally, Zhang, Wang, and Wang [302] again extend the work in [300], but use a multiple binary barrier option in a Monte-Carlo framework to value the contract.

5.6.2 Experience of Real Options in the Engineering Profession: Monte-Carlo Simulations to the Rescue

Real options have not been widely used in engineering practice [303, 304]. This is due to the fact that the real option analysis, especially when using closed from analytical solutions e.g. Black Scholes based formulae, requires an understanding of financial theory and advanced mathematical techniques. There are also other techniques such as decision trees, that can convey the same information albeit they ignore parameter volatility in the calculation. Monte-Carlo real option methods (see Glasserman [305], Judd [306], Dunn and Shultis [307], and Brearly and Myers [81], for texts on the subject) provide engineers with a much more tractable way of developing such an analysis – it can be argued that it is easier to understand especially by corporate senior management, albeit these models can be complex.

5.6.3 Using Real Options for Portfolio Management

Note it is standard practice in financial portfolios to have combinations of futures options and other derivatives. Option theory can be used to value risk, and utilized to hedge asset portfolios. In addition it can be used to select an optimal portfolio based on a basket of KPI's[111] and other constraints [308]. Representing real assets as options fits directly into the framework for risk management of such assets.

[111] Key Performance Indicators.

5.7 Option Pay-off

The key in developing a real options approach to aggregation is to recognize that the payoff functions[112] of aggregators resemble those seen in option theory. Payoff graphs are the graphical representation of an option's payoff. The x-axis represents the call or put option's spot price (P_x), whereas the y-axis represents the profit/loss that one reaps from the option. The y-axis (V_y) is evaluated using the value of the option. Values are calculated for many P_x and plotted accordingly. In the case of simple or vanilla put option this value would be:

$$V_{y=} \max(0,\ K\text{-}P_x) \tag{5-5}$$

where:
V_y – Pay-out of option.
K – Strike price or threshold of option e.g. the level of the guarantee or insurance level expressed in £/MWh.
P_x – Price of the underlying – e.g. the clearing price in this instance.

In the case of options that are more complicated ,the pay-out function equation would be modified accordingly (see Haug [309]). Equations (4-1) – (4-3) in Chapter 4 provides a representation of payoffs in this work and Figure 5-4 shows them graphically.

It has been recognized that the payoff associated with the various business models that have been investigated are akin to vanilla call options and a up and out digital option (see Figure 5-4 and Wilmot [256], Ravindran [310]). However, the situation is

[112] A payoff function is mathematical function describing the award given to a single player at the outcome of a game. In options terms it is the payoff that one receives as the price of the underlying commodity changes e.g. power price and is usually depicted graphically as pay out vs commodity price.

more complicated than that, because the aggregator options are exotic options with multiple underlying asset movements that are correlated (see below for explanation). They therefore cannot be modeled accurately using closed form[113] solutions for either a vanilla option, or the standard approach for up and out digital options.

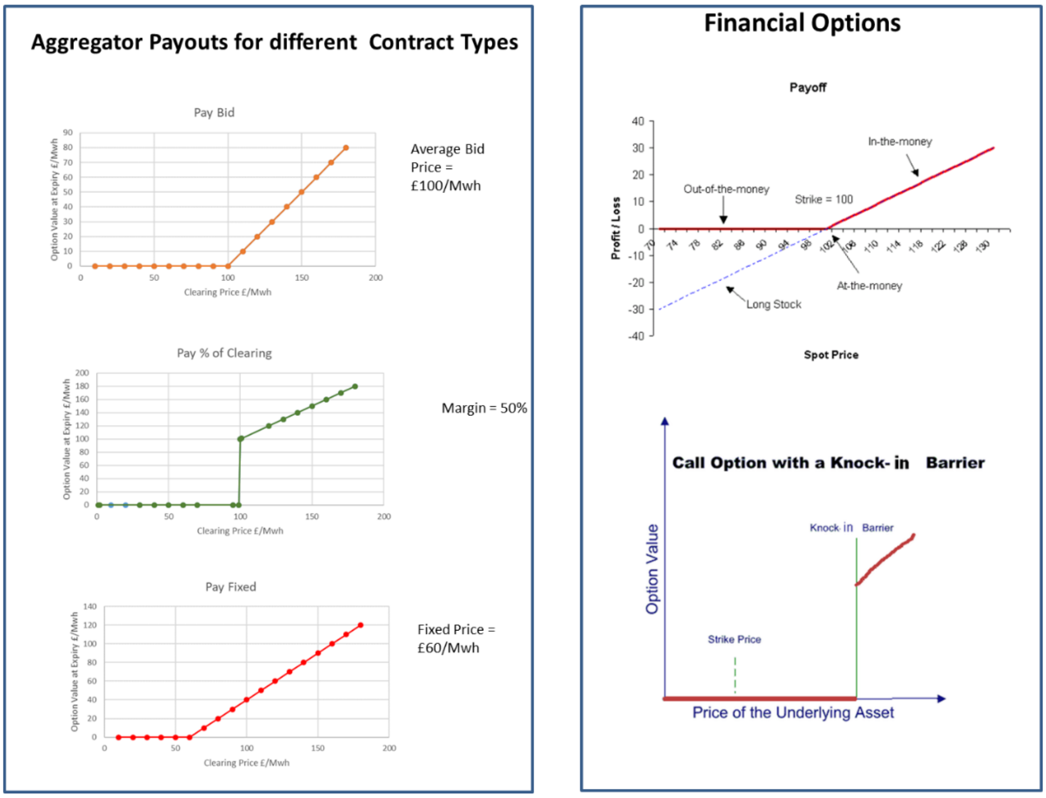

Figure 5-4: Payout diagrams for aggregator revenue business models presented in Chapter 4

5.7.1 Exotic Options

The option framework developed for the aggregator below shows that it belongs to the class of correlation options known as an exotic option [257]. That is, price movements associated with multiple assets or commodity prices are correlated. For example, spread options used to represent power options [279] use the price of gas vs

113 That is, an analytical approach.

the price of electricity. These two prices movements are typically correlated in some way[114].

Many papers investigating energy retailers[115] for example, explore the use of interruptible contracts, which by their very nature rely on a single underlying asset i.e. commodity price movements on only one asset [300-302]. The aggregator problem presented herein is a three-asset problem with moving parts in the customer bid prices[116], clearing prices and the volumes (MWh) involved in the option. The option could be characterized as a mixture of a spread option and a product option [257]. Valuing such options is analytically complex[117]. So numerical methods such as Monte-Carlo are typically used. This also has the benefit that it more understandable to the engineering community as well as to senior management [280]. The Monte-Carlo method allows analysts to create sophisticated solutions for exotic options but requires longer compute times. Option Greeks[118] (see refs [249, 256] for a fuller discussion of the definitions of option Greeks) can be calculated from the simulations using methods like those laid out in [309]. Normal VaR can be calculated directly from option deltas and the VaR can be used in hedging.

Option deltas and in some cases delta and gamma can also be used in dynamic

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[114] At certain times this may not be the case but gas powered generation in many markets represents the marginal plant cost.

[115] Also known as load serving entities LSE in some of the papers. See papers referenced above.

[116] Customers are bidding flexibility – volumes and price

[117] With the appropriate approximations, it may be possible to develop an analytical solution but this is beyond the scope of this thesis.

[118] Greeks represent sensitivities in the value of an option with unit changes in price, volatility time and discount rates. The two key Greek measures that will be discussed in this thesis are delta (change in value of option with price movements and gamma (the change in delta with price movements)

and static hedging strategies for a portfolio of options

As discussed, dynamic and static hedging of portfolios with vanilla option contracts is the norm in finance. Such techniques can be extended to exotic options, but there are challenges [257] (ch 35). A review of portfolio selection methods is given in [311].

5.8 Aggregator Risk: Three Asset Exotic Option

Aggregators face risk because clearing prices, (CP's) will be uncertain and volumes bid by customers may change[119]. In formulating bids it is assumed in this thesis, that aggregators apportion bids to one of a number bid buckets. Using the buckets average bid prices as a base, aggregators adjust the bid prices to create final bucket bids (volumes and price) [120]. A change in volume because of an issue at a household would effectively change the make-up of a bid bucket. The aggregator may need to source a more expensive customer to make up any non-delivered volumes. This risk can be represented as a change to the average price bid by the various customers and the volumes inside the bid bucket. Of course non-performance by customers could be managed with appropriate contractual arrangements i.e. penalties. Ignoring penalties, the aggregator faces risk in three interacting and correlated variables, namely clearing price, volumes and bid price. That is, it is an exotic option based on three variables.

[119] Customer volumes may not be available.

[120] Bids are aggregated into bid buckets as described in section 2.7.

5.9 Using Options to Value Risk in Aggregator Operations

Although it would ideal if these aggregator options could be represented using analytical solutions, this can only be achieved by assuming the driving parameters are independent and normally distributed[121]. Unfortunately, this is an unrealistic assumption, as clearing prices will be related to bid prices and they will be correlated with each other in some way. Other contract types could be more complicated. This has driven the author to develop an approach based on a Monte-Carlo numerical valuation of three interacting assets developed originally developed by Haug [309] (p 352 section 8.1.4) and adapted by the author (see Appendix D for pseudo code). In this context, clearing price, customer flexibility volumes (MWh) and bid prices (£/MWh) are the equivalent of the three asset prices in Haug's original model.

Note Green and Wicksell [312] develop a closed loop analytical solution for a three asset spread option. This is not quite, what is required to value an aggregator portfolio, but a similar approach may prove worthwhile in the future.

5.9.1 Additional Benefits of a Numerical approach to Valuing an Aggregators Portfolio

The Monte-Carlo numerical approach provides additional benefits. These include:

- Rather than simulating paths of prices using geometrical Brownian motion, mean reversion or some other distribution as typically performed in closed form solutions, it is possible to select from the probability distribution of

[121] We can derive one equivalent standard deviation sigma from the combination of more than two others and then utilize analytical solutions using product or spread options.

final prices directly. Historical probability distributions would be available to aggregators operating in the market (or by simulation). Use of a copula distribution [286] may provide more accuracy and granularity to the probability distribution[122]. Such an approach was used by Hawas and Cifuentes [303] in simulating a real option on large construction projects. An approach similar to that outlined in [303] could be used in the ABM simulation model, but a simpler approach based on simulated data is used.[123]

- CVaR and VaR can be directly estimated from the simulations used in calculating the option using the three-asset simulation discussed above, using an approach outlined in [313].

Utilizing an option based approach, using the three uncertain inputs (CP, average bid price and volumes), it is possible to construct risk valuation curves under different assumptions and compare the various contractual approaches discussed in Chapter 4. As with any put option when CP's are much higher than bid prices, the option would be deep out of the money so the option would be worthless[124]. In the case where CP's

[122] The copula allows the use of multidimensionality in probability. Probability associated with clearing price would be dependent upon demand and or other variables and so a copula recognizes the inherent correlation between price and expected demand. The copula essentially has different probability distributions for different levels of demand or ranges of demand. For example,. we expect demand to be within X-Y. What is the probability distribution of the clearing price for this demand range?

[123] Uses demand to select an average of historical clearing prices – a simple copula.

[124] For the pay as bid contract.

are much lower than bid prices the option is “deep in the money” (CP<<bid price), and the put option value would simply be (average bid price – clearing price)* volume[125].

The value of the put option represents the risk premium required to meet some threshold In this case the threshold is some minimum profit level expressed as an equivalent £/MWh. Risk premiums associated with this analysis of are therefore a function of the following parameters:

- Volatility in clearing price.
- Volatility in effective outturn bid price due to change in volumes by customers to accommodate changes in actual volumes sent.
- Volatility of volume of bids accepted – will be different for different buckets – driven by customer choice.
- Expected clearing price E[CP][126].
- Expected bid Price E[Pbid].
- E[Profit margin] – profit threshold set by the company.
- Margin - % of the clearing price retained as a profit.
- Operating cost expressed as a unit cost £/MWh -OPX – note depends on number of customers and their average flexibility load delivered.
- Annualized Capital Cost expressed as a unit cost £/MWh – CPX.

[125] Assuming volume is fixed. Volume is not fixed so this is a slight oversimplification.

[126] Note E[] is used to note an expected variable or parameter.

In the section below simplifying assumptions are made on the option to be valued, so that comparisons can be made about the relative risks in the various revenue models presented in Chapter 4. This section assumes that the aggregator collates all bids into one bin. In practice each bin or bucket as discussed in [82] (and also section 2.7 and Appendix N) would be treated as a separate options and summed to obtain the overall risk. Delta and Delta/Vega hedging in this instance could be used to hedge the combined effect of the bins.[127]

5.9.2 Downside Risk: Comparison of Business Model Risk Premiums

As discussed put options can be used to value the insurance premium that one would need to pay in order maintain a minimum profit margin. Essentially the value of risk of the bucket in this instance. In an option, this threshold is modelled using a strike price typically represented with the symbol X or K. Using assumptions and values set out in chapter 4 as a guide, the value of aggregator put options, for the three revenue cases, are shown under different assumptions. Exotic put options have been assessed for a variety of parameter inputs and the results are summarized in Figure 5-5 and Figure 5-6[128]. The margin in the pay % of clear price case is assumed to be 35% to the aggregator. CPvol – is the clearing price volatility, Bidvol is the bid price volatility. Volatilities are hourly volatilities. A profit margin threshold is set at a fixed value £10/MWh[129] and is used as the strike price (min profit threshold) for the

[127] The bins are in effect a set of options, just as the power plant in [284] option. This allows techniques used by the financial industry to hedge such a portfolio of options.

[128] Note CPX, OPX is ignored in the option analysis.

[129] 10% of the bid price.

options.

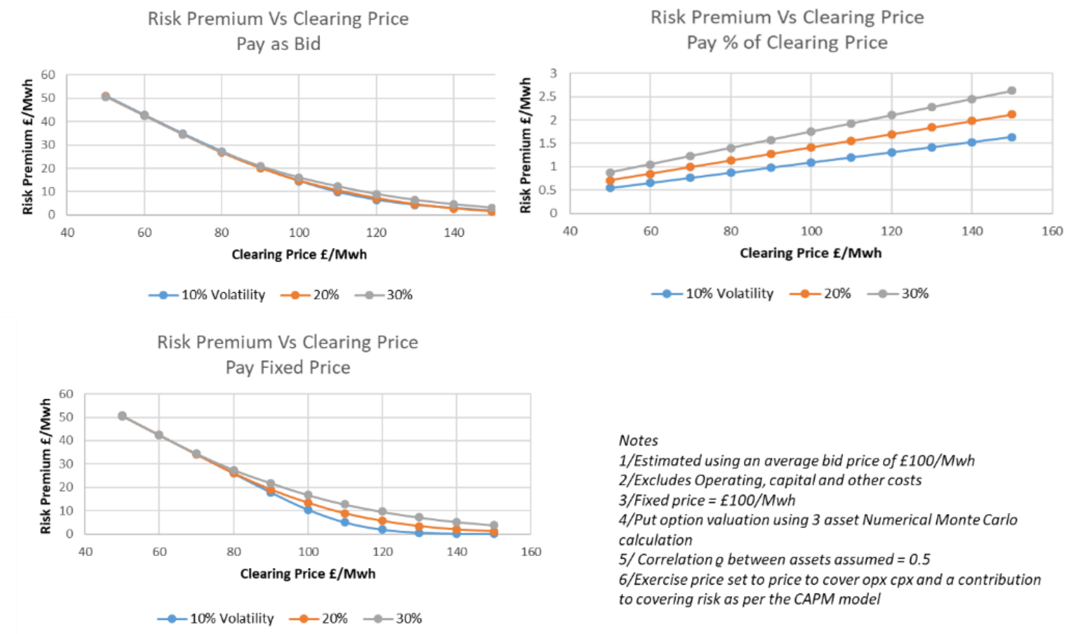

Figure 5-5: Aggregator put option value - Risk - (£/MWh) for three business model cases

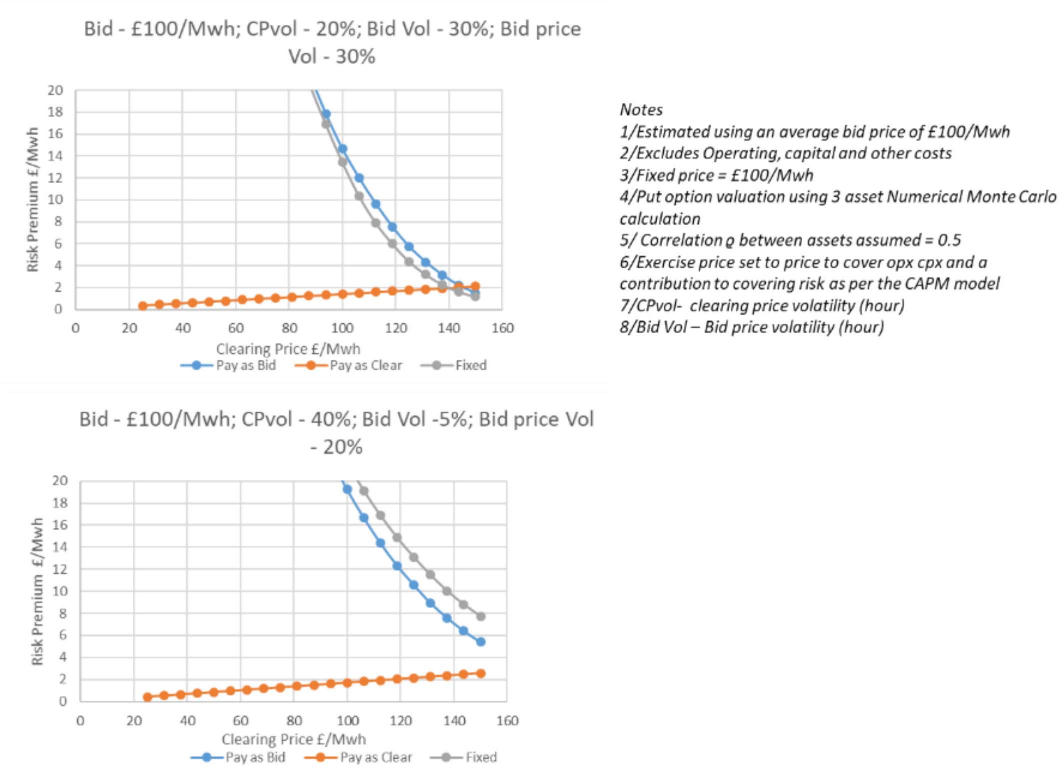

Figure 5-6: Contract business model comparison using put options with different volatility assumptions

Figure 5-7 shows how option values increases as the minimum profit margin requirement, as a percentage of expected clearing price, increases from 10 to 30%[130].

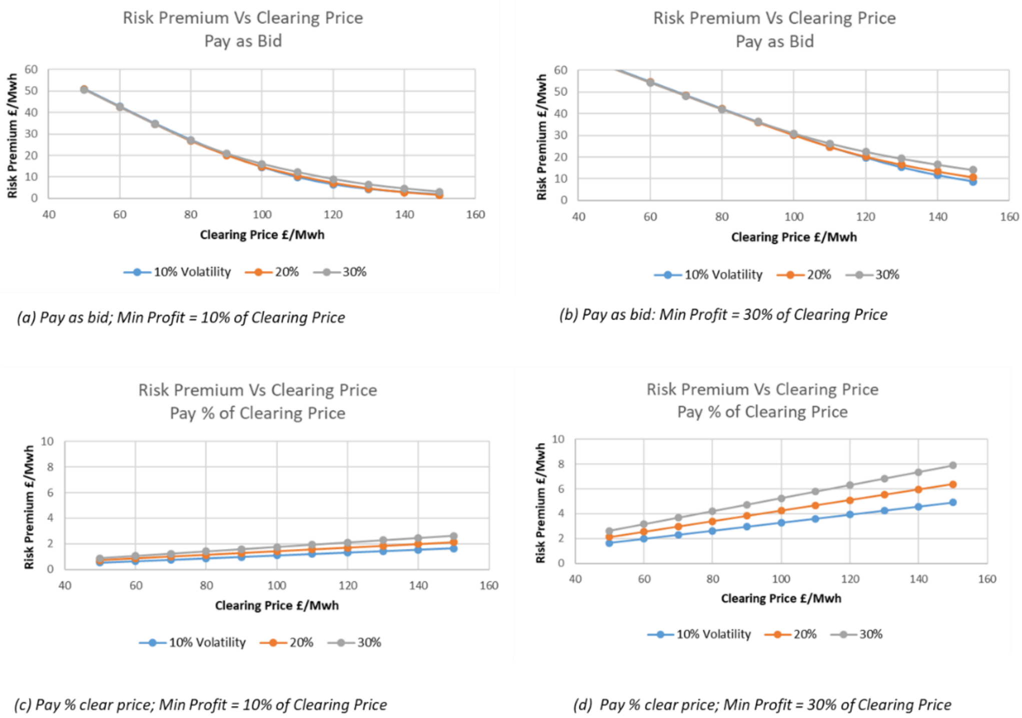

Figure 5-7: Aggregator put option comparison: 10% vs 30% profit margin requirements

Note that the shape of the pay % of clear price option is linear and has a positive slope albeit values are small in comparison to other models. This is due to the fact, that profit in this instance is related only to the clearing price. The higher the clearing price the more risk the aggregator takes. Aggregator margins affect the option value and when aggregator margins are low it faces more risk[131] that it will not meet its profit margin threshold. Higher volatilities result in higher risk premium as with any option and the pay as bid option has less spread than the other contract types. With

[130] With a fixed price of £100/MWh this equates to a minimum threshold of £10 – £30/MWh.

[131] 10% in the case shown. Higher margins result in the aggregator having less risk as they generate more profits. When the margin is set to < 1% option values rise to values approaching £20/MWh.

higher volatilities in clearing prices the fixed contract has more risk to the aggregator (assuming average bid price = fixed price). This is because the model assumes no risk associated with fixed price. Movements in CP are not cancelled out by movements in fixed price as they would be with the bid price case.

5.9.3 Estimating the Exercise Price for the Aggregator Option: Using ROE and Profit Margins

The value assumed for the exercise price of an option is a key element of the valuation. In the case of an aggregator, profit margin, seems an appropriate measure for this element. Return on Equity (ROE) is a similar measure to profit margin and can be derived by using the capital asset pricing model [314].

The Capital Asset Pricing Model (CAPM) model was the first coherent framework for answering the question how is risk related to corporate returns. It was developed by Sharpe in 1964 [315] states that the

$$\text{Return on Equity (ROE)} = \beta * (R_m - R_f) + R_f \qquad (5\text{-}6)$$

Where:
R_f – risk free rate or treasury rate
R_m - the average market return rate
β – Beta for company or stock/share

Beta (β) represents the company's riskiness when compared to the "average" company in the market ([81] Ch 9). A company's risk management stance would be reflected in the beta (β) seen in the market place assuming the company were traded. A β of 1 represents the market average so a Beta greater than one represents a more risky company. β is also related to the volatility of earnings. Power utilities with little or no risk typically have a β of around 0.5.[132] More risky companies might have a beta that is nearer 1.5 or 2.

The UK FTSE100 is a good surrogate for the average market return R_m in the UK. "Over the last 119 years UK equities have made annualized returns of +4.9% over and above inflation. Therefore, if inflation is assumed to be 2.5% on an ongoing basis, long-term returns would be ~7.4%. Over the past 10 years, the compound return was 8.8% per annum" [318].

Market Returns over the last 5 years have been low (4.4%) due to uncertainty in the market such as Brexit. The previous years yielded an average return of 13.4%. In the analysis that follows a rate of 13.4% has been assumed.

The UK treasury rate (or the equivalent of R_f) in 2019 was reported at 0.56% (Bloomberg 5 year gilt 11 Nov 2019 [319]) and has been used in the analysis.

Using standard accounting definitions of net income, profit margin and ROE, Profit margin can be expressed in terms of expected revenues, costs and equity. ROE is related to Profit margins by the DuPont equation/model [320][133] and can be estimated using CAPM as discussed above. Equations (5-7) – (5-10) set out the detail of these definitions. These equations will be used to estimate the profit margin threshold required by the aggregator and are coded inside the aggregator agent discussed in chapter 7.

[132] Values for Beta for different types of customers can be found at [316, 317]

[133] See also equation (5-10) below.

$$NetIncome = \frac{(\mathrm{Re}venues - COS - OPX - Depr) * (1 - tax\_rate)}{\mathrm{Re}venues} \tag{5-7}$$

$$Profit\ margin = \frac{NetIncome}{\mathrm{Re}venues} \tag{5-8}$$

$$ROE = \frac{NetIncome}{Equity} \tag{5-9}$$

$$Profit\ margin = \frac{NetIncome}{\mathrm{Re}venues} = \frac{NetIncome}{Equity} * \frac{Equity}{\mathrm{Re}venues} = ROE * \frac{Equity}{\mathrm{Re}venues} \tag{5-10}$$

where:

$Depr$ - Deprecation. Assumed straight line depreciation over 10 years – so Depr = CPX/10

ROE - Return on Equity

OPX - Annual Operating costs

tax_rate - Corporate tax rate %

$\mathrm{Re}venues$ - Clearing price * Volumes summed over year

COS - Cost of Sales – Payments paid to customers for bidding

Equity can be extracted from corporate accounts (balance sheets) and would vary through time as profits are transferred to the shareholders account in the balance sheet. In the analysis that follows, it is assumed that equity will remain constant and that all profits are paid out as dividends. At the inception of the company, monies will be required to put aside for hardware software and payroll costs. With no debt, equity would therefore be related to the capital costs of running an aggregator business and a proportion of payroll costs. For the ease of understanding the analysis below assumes equity = 1.1 * Capital costs to cover for working capital.

Table 5-1 below shows the yearly profit margin associated with different levels of β for a 10,000 domestic customer aggregator business as discussed in in section 4.3. The table calculates profits for the company under different assumptions and provides an annual profit, ROE and the required minimum price required in the market to provide a return commensurate with the β in the market, according to CAPM. Corporate tax rates are assumed at 20%, clearing price margins have been set to 50% for illustration in this table, average bid price from customer is equal to £70/MWh and its assumed that only 14% of the average domestic assumption in the UK is used as flexibility[134]. Capital costs and operating costs are as detailed in section 4.3 are used[135].

Pay as Bid

Beta	ROE	Revs/yr	COS	OPX/yr	DEPR	Profit before tax	Profit after tax/Net Income	Required Profit Margin = ROE *Equity/ Revs	Actual Profit margin	CP required to meet min profit margin	Bid BE - Max Bid
0.5	7.44%	1680	392	526	114.1165	647.8835	518.3068	5.2%	30.9%	203.64	166.4
1	14.32%	1680	392	526	114.1165	647.8835	518.3068	9.9%	30.9%	221.51	148.5
1.3	18.45%	1680	392	526	114.1165	647.8835	518.3068	12.8%	30.9%	232.24	137.8
1.5	21.20%	1680	392	526	114.1165	647.8835	518.3068	14.7%	30.9%	239.39	130.6
2	28.08%	1680	392	526	114.1165	647.8835	518.3068	19.5%	30.9%	257.26	112.7

Pay % of Cleared Price Margin % = 50%

Beta	ROE	Revs/yr	COS	OPX	DEPR	Profit before tax	Profit after tax/Net Income	Required Profit Margin = ROE *Equity/ Revs	Actual Profit margin	CP required to meet min profit margin	Min Margin BE
0.5	7.44%	1680	840	526	114.1165	199.8835	160	5.2%	9.5%	267.27	44.5%
1	14.32%	1680	840	526	114.1165	199.8835	159.9068	9.9%	9.5%	303.03	50.5%
1.3	18.45%	1680	840	526	114.1165	199.8835	159.9068	12.8%	9.5%	324.48	54.1%
1.5	21.20%	1680	840	526	114.1165	199.8835	159.9068	14.7%	9.5%	338.78	56.5%
2	28.08%	1680	840	526	114.1165	199.8835	159.9068	19.5%	9.5%	374.53	62.4%

Table 5-1 Relationship between ROE, CAPM Beta, profit margin and the minimum prices required by a power aggregator (CP – clearing Price, COS – cost of sales)

Figure 5-8 shows how the breakeven prices or the minimum clearing price to meet the profit margin requirements, changes with different assumptions; Beta, the numbers of customers and bid price. This graph is for the business model that pays the customer

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[134] Only 50% of the volumes in reference [77] are assumed to be flexible in this instance.

[135] Capital costs have been annualised.

its bid price.

Figure 5-8: Minimum clearing price required by aggregator to meet profit margin requirements for different CAPM Betas

The minimum clearing prices represent the thresholds that an aggregator company would require to meet ROE targets and hence profit margin targets and are used as the exercise price in the option models used in the simulations in chapter 8.

5.10 Portfolio Management and the Selection of Aggregator Business Models

It is clear from the preceding analysis that different revenue business models result in different risk reward profiles. The choice between risk, and not risk managing, is a personal one and depends on the individual preferences (risk tolerance) of these companies. This will impact the choice of business model. Standard financial portfolio management provides a framework on which this choice can be assessed. In addition, the use of utility theory and risk aversion coefficients allow for a comparison of business model choices and is used in the ABM framework discussed in Chapters 7 and 8. This utility value is used by aggregator agents to select the business models. In the sub-sections that follow an introduction to the portfolio management concepts used in this model are provided. Finally a model is specified that uses the value of the put option to calculate a utility value.

5.10.1 Portfolio Approach: Risk Reward

In 1959 Harry Markowitz developed his mean variance risk framework [321] for portfolio selection. In this work, Markowitz developed the concept of the efficient frontier to develop the idea that investors could combine different assets in different ways to produce a risk reward curve that represented the greatest value or reward for the some set risk level; or for a set reward what is the portfolio that provides lowest risk.

Typically, reward is represented as returns[136] and risk as standard deviation in expected returns expressed as a percentage, but can be shown as absolute values (Figure 5-9). The efficient frontier is the set of optimal portfolios that offer the highest expected return for a defined level of risk or the lowest risk for a given level of expected return.

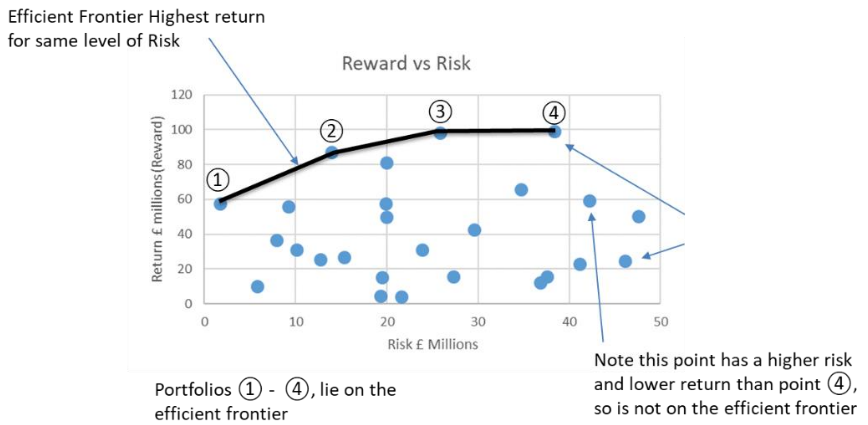

Figure 5-9: Efficient frontier example

Portfolios that lie below the efficient frontier are sub-optimal because they do not have enough return for the level of risk. Portfolios that cluster to the right of the

[136] Profits margins have been used in this work instead of returns.

efficient frontier have a higher level of risk for the set rate of return. Which a particular investor prefers is a matter of choice dependent upon the investors risk preference or tolerance. Economics usually deals with this dilemma using utility theory. Utility is a method that allows one to compare different risk reward values as one value (see [322] for a fuller discussion). It was first developed by Daniel Bernoulli in 1738 to represent risk aversion in consumers [323]. Utility represents the reward on a "risk adjusted basis" depending on exactly how the individual sees the value of risk. Typically, the concept is used in economics and uses indifference curves or Utility wealth curves [324, 325].

5.10.2 Levey and Markowitz Extension: Combining Portfolio management with Risk Aversion

Building on Markowitz's original work in 1959 on portfolio selection, Levy and Markowitz [326] extended the framework to look at portfolio choice using utility theory. By combing the work with Arrows Risk aversion coefficient [327](Lecture 2 - The Theory of Risk Aversion p 28)] the authors develop the relationship shown in equation (5-11).

$$U = E(r) - 0.5\lambda\, \sigma^2 \qquad (5\text{-}11)$$

where:

U – Expected utility
E(r) - Expected return

λ – Arrows Risk Aversion Coefficient[137]

σ^2 – *Variance of returns*

The part of the equation to the right of the "minus" sign indicates the risk of the portfolio itself, taking into account the investor's risk aversion. The formula as a whole therefore gives us the difference between the total expected return of a portfolio and the risk involved. In fact, by subtracting risk from the expected return E(r), one gets the return on a risk-free investment

With λ=1 the investor is considered risk neutral and the utility U represents what is known as the certainty equivalent value (Expected Return – Value of Risk) . With λ <1, U represents the utility as seen by a risk loving investor. At λ=0 the investor doesn't care about risk and would select project based solely on the profit regardless of risk. This would mean that non-hedged strategies would always be selected.[138]

Various authors have over the years have criticized the Levy Markowitz approach; even Markowitz recognized that variance (σ^2) did not necessarily reflect the views of actual portfolio managers. He expanded the work to include semi variance measure which is the variance based on downside variations [321].

5.10.3 Fishburn's Generalized Mean Risk Model

Fishburn [328] developed a utility model for risk aversion that included downside

[137] Note the Risk Coefficient applies to Arrow's CARA model, which assumes constant absolute risk and does not recognise that the accumulation of wealth may in fact change investors risk preference. This model has only one factor whereas other more sophisticated models use multiple factors and make them more complex to use. For the purposes of this work, the CARA model is used.

[138] The hedged position is the unhedged position – cost of hedging.

risk. It is a generalized model that uses two parameters to define utility. By extending Markowitz's and Levy's work, Fishburn developed a generalized model he called the "mean-risk dominance model"; the so called a-t model. The model considered downside risk as opposed to variance (which is a two sided concept) in which risk is measured by a probability-weighted function of deviation. It used two variables "t" (a threshold value – a target value) and "α", a risk aversion coefficient. A special case of the α - t model is the mean-target semi-variance model developed by Harry Markowitz when $\alpha = 2$.

As discussed by Fishburn, given a threshold "t, α is supposed to reflect the decision maker's feelings about the relative consequences (personal, corporate, etc.) of falling short of t by various amounts. If his main concern is failure to meet the target without particular regard to the amount, then a small value of α is appropriate. On the other hand, if small deviations below target are relatively harmless when compared to large deviations, then a larger value of a is indicated" [328]. In essence, this fits well with the idea that aggregators will be looking to achieve a minimum profit level.

It is important to note that these various models have limitations and have been criticized in some way or another, e.g. the Fishburn model ignores correlations between assets. However as Fishburn suggested his generalized model can be used to represent a variety of different risk aversion stances by changing the alpha α and the t constants.

The key here is different aggregators or investors in general will use different decision-making models in the selection of their aggregation portfolios. The utility approach allows us to convert risk and reward values into a single figure so that they can be compared. Different models will result in significantly different utility values and will therefore affect choices.

5.10.4 Ang, Chen and Sundaresan, "Liability-Driven Investment Model with Downside Risk”

Ang, Chen and Sundaresan [255], in the context of evaluating pension liabilities and their downside risk, derive a model that incorporates a put option in its formulation. The utility of the portfolio return is shown in equation (5-12).

$$U=E(r) - 0.5\lambda\, \sigma^2 - CV_{put} \qquad (5\text{-}12)$$

where:

U – expected Utility
E(r) – Expected return
λ – Arrows Risk Aversion *Coefficient*
σ^2 – Variance of returns
C - Coefficient set to 0-2
V_{put}– Value of put option

Unfortunately Ang, B. Chen, and S. Sundaresan do not provide any views about what value the factor C should take, but show its affects from values ranging 0 - 2. In the context of the aggregator problem discussed herein, values greater than 1 do not provide interesting results, so a value of 0.5 has been used in the simulations presented in Chapter 8.

Other researchers have developed alternative approaches. Ang [329] (Ch 4) provides a useful discussion of different risk stances and models that one could use to represent downside risk. This is still an active area of research but mainly focuses on finding an approach that would select superior portfolios. This of course would also be a future research avenue for aggregators searching for a superior selection algorithm.

As the business models in this thesis result in different risk/reward profiles the Ang, Chen and Sundaresan model using a C=0.5 has been used to compare models in the simulations presented in Chapter 8. The single value obtained from equation (5-12) thus allows the aggregator agents to choose between the various business models with different risk reward profiles.

5.11 Chapter Summary

Payout functions (equations (4-1) – (4-3)) developed in Chapter 4 and shown graphically in Figure 5-4 can be represented as a financial call option. In addition, downside risk can be represented by put options, the value of which would represent the insurance premium that would be required to be paid to cover such risk. This allows analysts to simply model a full hedge of the aggregator's risky position, but assumes that the option can be purchased in the market.

Valuation using an options approach allows for practical risk control measures using Delta or Delta/Gamma approaches to be used. This is somewhat easier to understand and implement than the alternative approach of CvaR or VaR. Such option techniques are leveraged in Chapter 6 and 7 to model an aggregator agent's risk and the effect of simple hedging strategies on market dynamics. Note that the development of a three asset put option to represent downside risk associated with an aggregator is an original contribution to research.

Key Points

- That expected payoffs of the three revenue models can be represented as options.
- Monte-Carlo techniques or numerical trees can be used to calculate the value of these options, and used as financial instruments to hedge risky financial positions.
- That the three revenue models investigated have different risk premium structures although fixed and pay as bid revenue models can be very similar under certain conditions.
- That hedging can be valued using a put options approach.
- That the methods set out in this chapter can be used to value other power business models (BM).
- Additionally, BM's will exhibit different risk and reward profiles. The use of portfolio concepts using "Utility" can be employed to select an appropriate BM.

Chapter 6

Human like Customers: Model Frameworks, Emotions and Social Interactions

This Chapter introduces the modelling of customer interactions in the context of this thesis and reviews modelling and theoretical literature on representing human behaviour and especially emotions in silica. This is a vast research area, firmly rooted in the Social Sciences, but computational modelling of these effects is a relatively young science that still faces many challenges. Development of an approach that can represent human behaviours in a power setting is an important contribution to the art, as current tools do not adequately represent human or aggregator behaviour in their models. This is an important for a number of stakeholders including regulators, customers, aggregators and the DSO's.

In addition, modelling social interactions is important as "Energy is consumed in social environments and in the presence of social peers. But social interactions do not just happen alongside energy behaviour - the two are intrinsically linked."[14]. Social science researchers have started to develop conceptual frameworks to capture these social dynamics [15-17, 330], but no computational model incorporating emotions and social interaction in the power aggregator domain exists at present. Creating a framework which can include power system networks, customers and their social relations with themselves and aggregator companies (and others) would be an important first step in providing a more holistic model of a low carbon distribution network. Without this aspect, policies would fail to take account of the impact of social interactions and customer psychology on system operation. As far as it is known, very little research has been performed on assessing this behaviour in the context of electricity market modelling, and none of it has addressed how customer behaviours would affect aggregator dynamics.

The Chapter is split into four main sections as follows. Section 6.1 introduces the abstract concepts of cognition, psychology and emotions, and reviews literature on computational social psychology and the representations of emotions in particular, in agent based models. Many of these abstract concepts focus on answering detailed psychological and emotional questions, where-as the remit of this work is to develop a model that represents human behaviour including emotions in an efficient abstract computational model. They are included for completeness and may prove useful in future work. Section 6.2 reviews how computational systems have represented bidding behaviour in models. This is important because customers, generators and the aggregators themselves are essentially bidding into a market. They will adjust these bids to take account of market conditions as well as competition effects. Section 6.3, introduces Social Network and Social Network Analysis (SNA), in the context of this work. This is important, as a social media will play an important part in the setting of prices and transmission of information about new services and offerings. Middlemiss et al., for example in a recent study, has shown that social media interaction plays an important part in low-income consumers taking up energy services [15]. In this regard, a multilayer "gossiping" network representation is introduced and is linked to the abstract representation of human behaviour developed later in the chapter. Social media networks based on Facebook/Twitter and a Watts-Strogatz small world network [331] have been used as a basis on which to simulate such interactions.

Finally section 6.4, details the extensions made by this author to Epstein's Agent_Zero framework [89] to accommodate economic assessments, customer emotions and social interactions. The framework keeps track of multiple emotions (anger and happiness) about the performance of six aggregators. This social, cognitive and economic framework has been selected to represent human behaviour in the model presented in Chapter 7/8. Currently only domestic customers have been provided with this behaviour. Future work could extend this to include other actors, although it is usually considered that corporate actors act more rationally. The structure of Chapter 6 is summarized in Figure 6-1. In particular, the Chapter provides the following important contributions to research:

1. The introduction of multi-layer social networks to propagate messages about the state of the market.
2. Extension of Agent_Zero framework to represent human behaviours (Emotive, Social and Cognitive) in a low carbon distribution network setting.

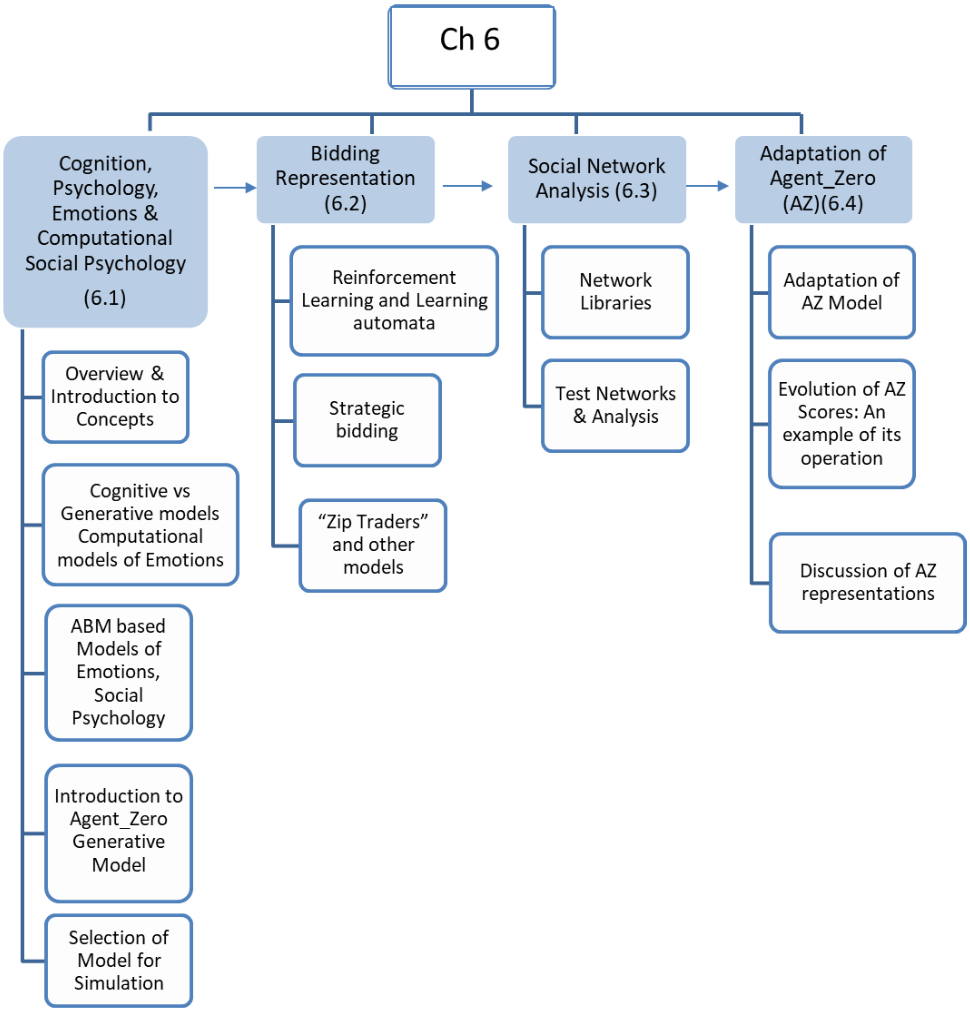

Figure 6-1: Overview of Chapter 6

6.1 Social Science: Modelling Customer Behaviours and Emotions

This thesis will focus on a case study involving customers that interact with aggregator companies in a low carbon power market. Customers will have feelings about these companies; some will be formed by their own opinions; some with closely connected friends and neighbours, and some from others further afield. However, how should these feelings/emotions best be represented and how will these emotions influence behaviour? Are there computational frameworks that can be used to represent them in this case study? What is the best way to do this?

The following sections introduce the theory behind psychology, social psychology and emotions. However this is not a thesis on sociology, social sciences or psychology, so the aim of this work is to find a suitable framework to represent one aspect of a very large field of research. In particular, the aim of this work is to:

- Represent interactions between customers using a social network to share views;
- Represent emotions in said customers using a simple and understandable but effective framework;
- Represent social impacts on said emotions and represent those emotions in association with logical constructs such as economic appraisals on assessing aggregation performance.

Much of the research from the social science and social psychology communities focuses on one aspect or one narrow specific question. Similarly, ABM's utilizing social constructs again focus on narrow representations. So many of them would not be appropriate for this work. Some like the CONSTRUCT [139, 140], Clarion [146-148], ACT/ACTR [151, 332, 333] or SOAR [142, 144, 145] models[139] provide too much detail potentially for this problem but may prove to be useful frameworks in future work e.g. CONSTRUCT for modelling organizational structures. Contact with the

[139] Note these are not all ABM models.

developers of CONSTRUCT by email indicates that it might be possible to use an XML file to exchange data between CONSTRUCT and the simulator proposed here, written in Python. Note however, CONSTRUCT was written to represent knowledge transfer and formation dynamics within organizations. At this point, it provides another level of complexity that is that is not currently required. However, in terms of modelling an "independent regulator" agent, for example, it might prove extremely useful.

The social sciences covers a wide range of theoretical approaches and can be diverse in its approach to representing various aspects of human behaviour. The various theories can provide a researcher with a diversity of insights but at the same time can be frustrating for a modeler/researcher looking to use these many theories as a scientific basis for their own models. Most researchers are drawn to the middle ground [334] (p65).

The key to selecting and using an appropriate theory or modelling framework is the idea that to help answer a particular modelling question researchers need to focus either on the intrapersonal (the mind and body of an individual), interpersonal (social), or the organizational (e.g. cultural, knowledge sharing) dynamics of the question at hand [335] (preface). Reference [336] proposes a conceptual framework for representing agent models in a military setting using three dimensions that represent <u>the social entity or granularity</u> (individual, cell, family, Tribe/Clan, Ethnicity, Nation/State, International); <u>the scope</u> (tactical, operational and strategic)) and <u>the time frame</u> (hours, days etc.). There are many different models all dealing with these various categorizations and with different questions in mind. None, as far as it is known, specifically focus or answer the questions that are posed in this thesis. They do provide potentially some useful building blocks with which to formulate a modelling framework focused on customer behaviours in a flexibility/aggregator market setting. Some of these frameworks e.g. for modelling organizations may be useful for future work.

Because there are so many different competing theories, it can make it confusing for the researcher to choose an appropriate theory or methodology. However, the following sections will try to summarize the key points that are appropriate to this thesis rather than provide a complete literature review of the social science discipline and its theories on human mind and behaviour. Readers are referred to texts such as [337-341], for a fuller treatment. In particular, few textbooks deal solely with computational social/psychological/organizational modelling approaches; references [335, 342-344] are recommended for the interested reader. Some of these texts are really just a selection of papers dealing with the diverse aspects of this research area. Most, if not all of these papers, are focused on social science issues.

In the context of human behaviour in power, models have focused on rational behaviour typically using marginal costs as the basis of their analysis e.g. like in the SmartNet project. Therefore, this section leans heavily on the ideas and experience of computational social scientists like Carey, Epstein, Read, Nowak and Vallacher.

6.1.1 Which model to Use? A Decision Framework

Carley and Newell's 1994 paper on the ideal model for a social agent[140], sets out a matrix of potential designs for social agents along two dimensions; knowledge (ranging from non-social agents through to modelling cultural history and Cultural exchanges and learning); and processing capabilities (rational, bounded rationality cognitive and emotional cognitive) [345]. It is a useful framework in that it shows the breadth of choices that a modeler has to represent social interactions and more generally human behaviour (see Figure 6-2).

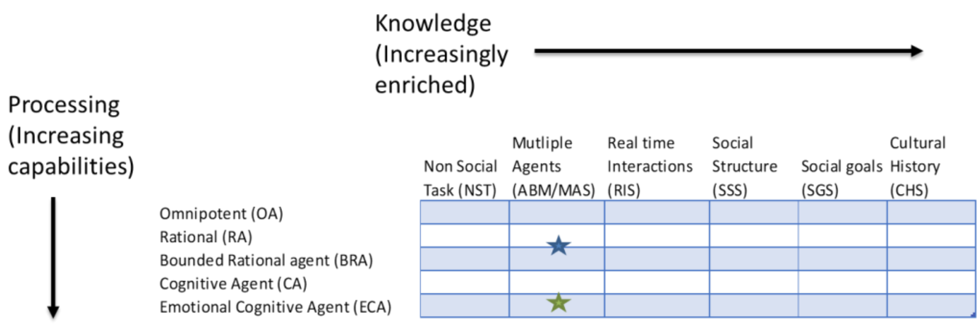

Figure 6-2: Model social agent;2D selection matrix; Adapted from figure 3 in [345]

Figure 3 in the same paper fleshes out examples of human characteristics in various cells of the 2D matrix e.g. group formation, scheduling, learning from others, sharing information, norm and ritual maintenance and so on.

This thesis requires an agent that can have emotions and interacts with other agents, sharing these emotions. Decisions on bidding and selection of options will be

[140] Note this is a conceptual framework.

rationally based (economics). Thus, in terms of the framework in Figure 6-2, (see Blue/Green stars), an emotionally cognitive/rational agent operating in a Multi-agent environment is required

6.1.2 Cognition, Psychology, Emotions and Social Theory

6.1.2.1 Psychology/Social Psychology

Psychology is the scientific study of the mind and behaviour, and includes many sub-fields of study, such as human development, social behaviour, and cognitive (thought) processes.

"Social psychology is the scientific study of how people's thoughts, feelings, beliefs, intentions and goals are constructed within a social context by the actual or imagined interactions with others ..It therefore looks at human behavior as influenced by other people and the social context in which this occurs." [346, 347].

Social psychology consists of three parts: affect (feelings), cognition (thought and mental process), and behaviours (interactions) [341]. It considers that human behaviour is both a response and a stimulus to the behaviour of others. That behaviour can be from visual cues, such as appearance, or from behavioural components – how one acts. This thesis focuses on behaviours observed on digital platforms such as social media.

6.1.2.2 Cognition/Social Cognition

Cognition is defined in the Oxford English dictionary as the "The mental action or process of acquiring knowledge and understanding through thought, experience, and the senses."

"Social cognition is a sub-topic of social psychology that focuses on how people process, store, and apply information about other people and social situations. It focuses on the role that cognitive processes play in our social interactions." [348]. In a computational sense, it would involve the modelling of thought process carried out in assessing a social interaction.

6.1.2.3 Rational Choice Theory

Rational choice theory is defined in the Encyclopedia Britannica as the "school of thought based on the assumption that individuals choose a course of action that is most in line with their personal preferences. Rational choice theory is used to model human decision making, especially in the context of microeconomics, where it helps economists better understand the behaviour of a society in terms of individual actions as explained through rationality, in which choices are consistent because they are made according to personal preference."

Rational choice is therefore a valid method by which one could model human behaviour. Using marginal costs and economic decision-making is a common method used in the analysis of power systems to model both bidding and investment behaviours. Coleman [337] uses this idea of greed, self-satisficing and self-interested agents, as the basis of his "Foundations of Social Theory". In this work, Coleman posits the idea that macro to micro to macro effects (the so-called "Coleman Boat" concept) are crucial to model, and in order to do so, frameworks are required that connect these different levels. He also provides the basis for modelling social constructs in Agent Based Models[141] with concepts like trust, agency, social capital, social exchange, norms and authority. Finally, Coleman developed a mathematical model,

[141] Coleman doesn't specifically discuss the use of ABM models but the concepts fit well with this particular modelling paradigm.

which he calls a linear system of actions that could be used in such an ABM. Timmerman [349] uses the linear system of action framework to create an ABM/Multi agent model which looks at policy decisions in an environmental setting. However, Coleman's work was heavily criticized as being too rational by the social science community [350].

6.1.2.4 Ecological Rationality

Overall, rational choice theory (RCT) focuses on internal logical consistency whereas ecological rationality targets external performance in the environment. RCT consists of making decisions in keeping with rules, irrespective of context. Ecological rationality, in contrast, claims that the rationality of a decision depends on the circumstances in which it takes place, to achieve one's goals in a particular context. Social settings matter. Dekker and Remic [351] define two types of ecological rationality. "The first type of ecological rationality (ER1) as used by Gerd Gigerenzer," (Psychologist – Fast and Frugal Heuristics) "refers to the use of cognitive strategies, heuristics in particular, in real-world decisions. The second type of ecological rationality (ER2) as used in the work of Vernon Smith," (Experimental Economist) "refers to the rationality of cognitive systems consisting of multiple individuals, institutions, and social norms." For a comparison/discussion[142] of the two views see reference [352, 353]. Both views can be used to inform economic modelling of human behaviours.

[142] Especially see table 7.1 in [352]

6.1.2.5 Belief Desire and Intentions (BDI)

BDI is a well-known mental state and rational model developed originally in Bratman's theory of human practical reasoning [354]. Beliefs represent the current state of environment, desires represent the ideal states and intentions the plans and desires that the agent is trying to action. Software models that use BDI as a basis effectively choose from a set of plans. The software agents spend time considering plans (choosing what to do) and executing those plans (doing it). Plans also have to be created. For a good description of BDI software agents and its link to theory see [355, 356].

The BDI rational mental state model is still widely used in many agents especially in robotics and Multi agent systems. It is considered a cognitive modelling technique– as it involves a sensing and then thought before action. It is also rational framework, but it is known that although humans are directed by rational decision-making, human behaviour is also emotional [357]. An emotional framework for extending BDI was proposed in 2007 [358] and 2014 [359], but doesn't appear to have been extensively used. The concept that BDI/cognition should be joined to an emotional model is an attractive one that will be discussed later.

6.1.3 Emotions

There are many theories of emotions with some appearing to be at odds with each other. For a historical review and overview of some of these theories see [360, 361].

These theories and models are the result of analysis of human and animal behaviour and measurements of neurological activity. Lange and James (1922) [362] were the first to propose that emotions were linked to neurophysiological drivers.

According to their theory, emotions are as a direct result of physiological stimuli not perceived events. Since that and over many decades various theories have been proposed that argue that emotions have a behavioural, cognitive and motivational link. Arnold [363] introduced the concept of appraisal in emotions, and Frijda [364], Smith and Lazarus [365], and Scherer [366], and Ortony Clore and Collins (OCC) [367] extended the concept to include cognitive appraisal of a situation. Cognitive appraisal is one of the more popular theories of emotion, that is used in modelling emotions.

Of course, emotions are not just as a direct result of appraisal and some primary emotions are considered to be driven by neurophysiological stimuli. Unfortunately, there is not yet a unifying theory that fully explains human emotion.

"In psychology, emotion is often defined as a complex state of feeling that results in physical and psychological changes that influence thought and behavior. Emotionality is associated with a range of psychological phenomena, including temperament, personality, mood, and motivation." [361].

Emotion theories can be categorized into three categories; psychological (responses in the body), neurological (brain activity) and cognitive – where thoughts and other mental processes are assumed to drive the emotional process.

According to appraisal theories of emotion (Cognitive), thinking must proceed emotion [368] [143], and involves a sequence of events that includes a stimulus, followed

[143] Lazarus theory of emotion.

by thought, which then leads to the simultaneous experience of a physiological response and the emotion.

6.1.3.1 Mixed Emotions

Human beings are complex organisms and can have mixed emotions e.g. be happy and angry at the same time[144]. It should be recognized that some theories of affect (Emotional response) postulate that feelings at opposite ends of the spectrum are mutually exclusive. This means that happiness and anger cannot be experienced simultaneously [369]. The Evaluative Space Model (ESM) [370], however, postulates that organisms can have mixed emotions with stimuli affecting different substrates in the neural pathways. Effectively you can have mixed emotions. The ESM model is a dimensional affect model. Models that treat mixed emotions as a separate discrete emotion have also been proposed[145] using a bipolar scale of -1 to 1 (see [371]). Berrios, Totterdell and Kellett's, meta-analysis on number of studies on mixed emotions "revealed a moderate to high effect size for the elicitation of mixed emotions ..There was no significant difference between studies that conceptualized mixed emotions using a dimensional or a discrete structure of affect" [369].

It is clear that emotions can be described either by a dimensional model or with a bipolar scale. More recent work [372], suggests that these two competing models may be related with, essentially, a primary and secondary effect. That is, under certain conditions the discrete model dominates and so on. Although it is not the purpose of

[144] Although some social scientists would debate this.

[145] Note basic emotions like anger fear happiness are discrete emotions, but a blended emotion could have its own discrete state.

this thesis to justify this, it is important to note that these alternative modelling paradigms could be used to represent emotions. Note, that a mixed emotion model with a [-1,+1] score has been chosen to represent consumer opinions of aggregators in this thesis.

6.1.4 Appraisal theory

Appraisal theory is the theory that emotions are "elicited by evaluations (appraisals) of events and situations. For example, sadness felt when a romantic relationship ends may be elicited by the appraisals that something desired has been lost, with certainty, and cannot be recovered" [373].

The Appraisal theory (of emotions) was developed to answer the following types of questions:

- *How can we account for the differentiated nature of emotional response?*
- *How can we explain individual and temporal differences in emotional response to the same event?*
- *How can we account for the range of situations that evoke the same emotion?*
- *What starts the process of emotional response?*
- *What accounts for irrational aspects of emotions? And so on.*

Many of the other models fail to address these questions but appraisal theory effectively differentiates Emotions by appraisals.

6.1.5 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) framework [374, 375] has been used in modelling consumer behaviour in the retail markets for some time. TPB allows for comparison between behavioral intention (e.g. supporting an environmental issue or buying a product or service) in terms of attitudes, subjective norm, and perceived behavioral control. It is essentially a three-dimensional model although sub-categories are provided in each primary dimension.

Reference [376] uses TPB to explain household electrical energy use intentions and behaviour in Australia. References [377, 378] use TPB frameworks to explain energy consumption behaviours in Malaysia and China. Huijts et al [379] used a TPB framework to explain that the intention to act in favor of, or against, a local hydrogen refueling facility is more strongly based on moral considerations or on self-interest.

6.1.6 TPB and Emotions

The theory of planned behaviour is useful as a framework at predicting customer behaviours but typically ignores emotions. As discussed, the three dimensions of attitudes, subjective norms and perceived behavioural control (PBC) are inputs to the typical TPB model.

However in a recent paper, Londono, Davies and Elms [380], consider the effect of negative emotions on consumer buying behaviour in a retail setting by extending the TPB framework, with an additional input related to these negative emotions. It is a simple addition to the connectionist TPB framework. This may prove to be a useful in future work. Note the TPB technique requires the collection, analysis of consumer data and behaviour patterns. Model linkages (strengths between inputs) in these models are typically assumed to be fixed.

6.1.7 Cognition and Emotions

Many of the computational models and theories treat cognition separately from emotions. However, emotions affect cognition and cognition affects emotions. Pessoa in [381] lays out his thoughts on how these functions in neurophysiological sense are combined in hubs present in the brain. Reference [382] provides a survey on, and short descriptions, of various computational frameworks, that have both a cognitive and emotional element albeit most are based on the cognitive structures (see Table 2 in this reference). Although not currently in a computational form, Lerner has developed a theoretical framework that predicts the effects of specific emotions on judgment and choice outcomes. The framework has been used to predict emotional effects on perceptions of risk, and for making economic decisions (See Figure 2 in [383] for the conceptual model developed by Lerner et al.) and may useful in the context of this work. As far as it is known none of the models discussed in [382] address risk which is an important element of the model in this thesis.

6.1.8 Modelling Social Norms

Social norms govern most of our life. Although individuals might be conscious of some norms, like queuing, most behaviour is relatively automatic. Social norms are informal understandings that govern the behaviour of members of a society and provide us with an idea of how to behave in a particular social group or culture [384, 385]. Although this thesis is not going to consider social norms at this point, its impact on behaviours may be useful in future work concentrating on group behaviours e.g. it is expected that customers/organizations will bid and provide flexibility in a certain way, subject to social norms.[146]

Examples of simulation that use norms in modelling behavioural interactions in a social setting are given in [386-391]. In these examples, agents learn from others agents and perceive norms. Reference [391] uses a norm based BDI agent based model construction, while [386] is potentially interesting as it models payment norms in an environmental conservation setting. In this, model agents change their actions to increase their utility and/or conform to social norms, which in turn may change social norms. Macbeth [171] began to investigate the use of norms in a MAS environment using reputation and trust as a way to help agents self-organize. Morales et al [392-394] built a norms learning engine that warrants further investigation as it “evaluates norms in terms of their effectiveness and necessity” in achieving coordination. Logic allows the model to add, generate /create, specialize, generalize rules and deactivate them. The model is continuously synthesizing norms represented as sets of rules and essentially explores and measures their effects offline, before rules are activated to be used in a traffic management system. The modelling of social norms in this framework should be considered in future work.

6.1.9 Symbolic and Non-Symbolic Representations (Connectionist Models)

The AI and computational science/research community is separated into two camps; those that use symbolic representations and those that use non-symbolic ones [395, 396].

Symbolic approaches like that used by Clarion, SOAR and ACT rely on acquiring

[146] Many customers/organizations may not follow these norms, so there may need to be a mechanism to penalise them.

knowledge; representing that knowledge as symbols and in lists. These systems typically use rules and rule based engines to process that knowledge to illicit actions and decisions. By supplying the model with information that they believe it should know, researchers define the limits of learning.

Non-symbolic researchers use approaches that try to mimic the human brain e.g. connectionist models (chapter 11 in [397]) using, for example, neural nets, deep learning and genetic algorithms [398]. They are typically considered a black box approach and can learn patterns potentially outside of the symbolic set up. There is no searching through lists or using rules, so connectionist models are usually computationally fast.

Symbolic approaches work well when the problem is well defined e.g. like a chess game and where systems are process oriented. Connectionist models are well suited to large-scale ABM environments as they are more computationally efficient than the equivalent symbolic approaches.

6.1.10 Hybrid Approaches

Hybrid approaches that combine both concepts could be also used [399, 400]. In this regard, a connectionist approach could also be used with the Agent_Zero framework discussed in section 6.4 as it could improve the representation of emotions within this framework, by adding additional emotional response drivers. Note this would be for future work.

6.1.11 Cognitive Vs Generative Models

Overlap between cognitive and generative social science is small despite a shared interest in human behaviour. Cognitive science focuses on formal accounts of human thought, action, and behaviour and sometimes includes neurophysiological modelling. Generative science [87, 88, 401] approaches the question of understanding social structure and dynamics using simple computational agents in a social context [402]. The Agent_Zero framework that will be discussed more fully later in the section 6.1.15, and 6.4 is a generative model while SOAR is an example of a cognitive model.

In a hybrid model Orr et al. [402] sets out their reciprocal constraints paradigm (RCP) theory which uses three components to model a social system. These components include an integrated cognitive system; a neurophysiological and social system with constraints. The conceptual model was developed to link cognitive and social simulations at different scales e.g. cognitive vs social actions.

6.1.12 Modelling Paradigms: Computational Social Science/Psychology

Zacharias et al [403] reviewed a multitude of individual, organizational, and societal modelling approaches in the military modelling domain and presented them using a similarity network approach. Osoba and Davis updated the diagram with some additional links, as shown in Figure 6-3, which is reproduced from Fig 19.1 [404] and adapted from Fig II.1 [403].

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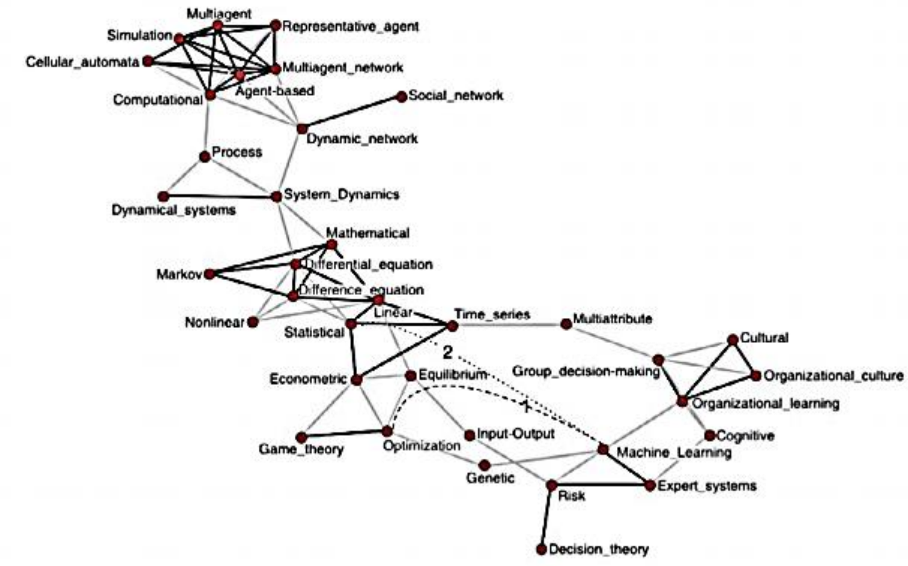

Source: Adapted from NRC report (Zacharias et al., 2008) p. 93

Figure 6-3: Similarity network of modelling methods: reproduced from Fig 19.1 [404] and adapted from Fig II.1 [403]

It is clear that many different methods could be used to model human behaviour, including in an electrical power domain setting. Many of these techniques have already been employed on their own [89], but many more could logically be used in conjunction with other techniques. For example, many ABM (or MAS) systems use optimization in their internal structure. In this work (discussed later), an ABM model with a simplified form of cognition, emotion, a social structure, and optimization, has been used[147]. This is important as future distribution flexibility systems will require the participation of new actors like domestic customers and aggregators. The behaviour of these actors will impact on DSO operation and their longer term planning and will impact on Regulator's market designs. Current tools do not adequately represent

[147] The Agent_Zero model uses a "simplified" cognitive logical and social model that is computationally light and therefore fast.

human behaviour in their models. This is also important for a number of stakeholders including regulators, customers, aggregators and the DSO's. The prior sections lay out the various approaches used in modelling detailed cognitive behaviours but are too complex and computationally inefficient for modelling the questions raised in this thesis[148].

In addition, other approaches are seen in the social science literature including the following examples: Systems dynamics (SD); fuzzy cognitive mapping, coupled oscillators, and connectionist models using emotion concepts.

The introduction of the effects of personality on emotions is developed by Read et al., in [405, 406]. In this approach, he uses the big five personality trait framework OCEAN[149] [407]. It is a detailed intrapersonal model of emotions, but because of its connectionist nature (i.e. neural net based approach), it might provide a useful addition to more sophisticated model of emotion in the future. Vallacher and Nowak's work focusses on interpersonal dynamics and on dynamic processes in social psychology [408], and in particular uses coupled oscillators to model interactions between individuals [335, 342-344]. Navarro-Barrientos et al., [409] used an interesting SD approach to model the TPB framework and although not specifically focused on emotions, it could prove a useful modelling framework in which to include them.

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[148] The scale of the problem used in the thesis (1000's of customers) would also result in large computation run times.

[149] OCEAN – Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism.

References [410, 411] present the use of Fuzzy Cognitive Maps (FCM) for modelling social processes in general and emotions in particular. Readers are referred to [335, 342-344] for more examples.

6.1.13 Computational Models of Emotions: Surveys and Examples

Bougais et al [412] provides a useful overview of modelling approaches used to capture emotions and includes ABM modelling approaches. Kowalczuk and Czubenko reviews 12 emotion modelling approaches mainly used in the robotic and chatbot field [413]. Lin, Spraragen and Zyda [382] review the research history of emotional computational models and focus on 3 "landmark" models, namely EMA, WASABI and Soar-Emote (PEACTIDM). Table 3 in this reference provides a useful list of modelling environments, comments and categorisations.

In particular, the reader's attention is drawn to the following key observations and tables from the three reviews listed above :

- Emotions can be represented as simple values (e.g. 0-1, 0-10), as vectors or in three dimensional space. For example, Adam et al [414] used two values; an intensity value and a duration value.
- Others use pairs of values like for joy/distress [415][150]. Some use symbolic representation with rule sets [416].

Table 2 in [412] provides a summary with references of the different models used and their approaches. Note that, none of these examples is from the electrical power

[150] This the approach that this thesis is utilising.

domain. Some use fuzzy methods others cognitive appraisal and some BDI with emotional modules.

Table 3 in [417] provides a good overview of models used to represent emotions, including the fuzzy logic based FLAME [418], EMA [38] (an emotional modelling extension to SOAR), Kismet [82], Mamid [419], Alma [39], Cathexis [37], PEACTIDM [52] and WASABI [420, 421].

Models are characterised along a number of dimensions including: perceptual processes; memory systems, behaviour systems, motor processes and emotion models. Figure 1 in [422] provides a useful categorisation (reproduced in Figure 6-4) of various computational emotional models by theory.

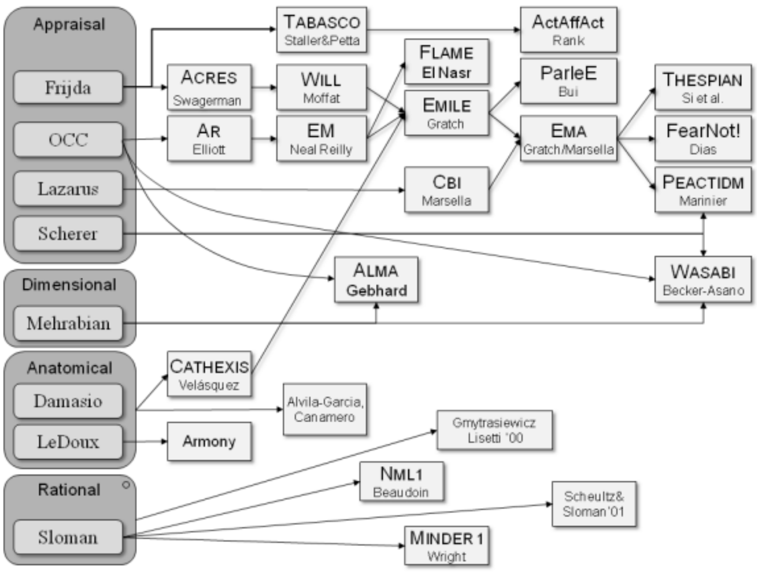

Figure 1: A history of computational models of emotion

Figure 6-4: Categories of emotional models by theory: Reproduced from figure 1 in [422]

It is clear from Figure 6-4 that many different theoretical basis are used in the various models and reflects the large and disparate views on the theory of emotions.

6.1.14 ABM Using Emotions in Energy/Power

There are only a few examples of ABM models using emotions in the energy sector or in power in particular. Many more can be found in the study of evacuation and crowd dynamics (e.g. [423]), and social sciences in general. Specific examples of the use of emotions in ABM Energy/Power can be found in [424-426].

Prosumer behaviour in emerging electricity markets has been modelled in a Netlogo Environment [424] using a social network. The work in [424] discusses emotions but represents them as a simple attitude equation. The attitude is towards the adoption of a contract. This work also focusses on the impact of environmental policy on prosumer uptake. The number of agents modeled is low (200-280) and no adaptive bidding is included.

Alyousef et al. [425], reviews the adoption of Solar PV and battery systems in Germany using an ABM framework and a simple assessment of the "affective" impressions (i.e., emotional sentiment) of the consumers on buying decisions. De Wildt and Chappin [426] used an ABM model to look at capability conflicts between households in a neigbourhood using a number of scenarios. The model included six agent capabilities including emotions and trust. Note that the authors stated that the simulation goal was not to "predict human or household behaviour and interaction".

Finally, Kran et al [427] developed a framework they called the Agent-Based Model of Critical Transitions, to explore the effects of heterogeneity, the effects of leaders, as well as network structure on the transition of energy markets. The work presented in the paper showed the importance of local communities and leaders in the energy transition process. The focus of the model was on developing behaviours associated with transitions using customer "utility" equations. The model makes use of the social aspects that Scheffer et al. [428] developed in their segregation model. The work highlighted that peer pressure, the absence of leaders, the complexity of the problem and homogeneity of the population are important in critical energy transitions. These are very different aspects from those considered in this thesis, but may be a useful addition in future work. The model is written in Netlogo and uses utility functions and equations to represent agents internal states and "call to action". The simulation uses 250 agents.

None of these models specifically model aggregators, and the particular research question posed here in this thesis, is not considered in these works. None of them link economic logic to social interactions and emotions in any sophisticated way.

6.1.15 Agent_Zero: A Generative Framework of Emotions, Social Influence and Cognition

"Cognitively plausible agents have emotions, they have bounded deliberative capacity, they have social connection, and all of these can interact to shape behavior. Accordingly, *Agent_Zero* is equipped with interacting emotional, deliberative, and social modules based in neuroscience" [429].

The book Agent_Zero [89] and follow up presentations and papers [429, 430] details the design and use of Agent_Zero in a Netlogo environment[151]. Framework case studies includes fight vs flight; the slaughter of innocents; a jury process; economic price cycle modelling and spirals of mutual escalation. It uses a generative approach[152] to provide social agents with simple cognitive abilities and emotional behaviors. A key element of this approach is its use of the Rescorla-Wagner (RW) model. The RW model has proved to be one of the most remarkable and influential models in psychology (Lieberman, 1990, p. 116[431]). This model [432] encodes some simple observations about learning and describes learning under Pavlovian conditioning [433] and a good explanation of the model is given in [434].

The RW model explains how organisms learn when events disrupt their expectations; and that the change of expectation depends on the difference between expected and observed levels, so that learning (or forgetting) will be rapid to begin with, slowing until it reaches a threshold or maximum value. It is often used in experimental psychological fields and it is used as the base model in the Agent_Zero framework to model the effect of stimuli on emotions. The RW model provides a simple interpretation of the complex behaviours involved in learning. However, it is not without criticism.

As Epstein points out, RW is not the only model that could have been used in the Agent_Zero framework, but provides a good starting point. For example Van Hamme and Wasserman [435] extended the RW model by adding new factors representing

[151] Supplemental material including the Netlogo models can be download from https://press.princeton.edu/books/hardcover/9780691158884/agentzero .

[152] It uses "simple" agent rules to elicit complex behaviours within an environment.

some of the failures associated with the RW model.

The base Agent_Zero model presented in [89] attempts to integrate social (S)[153], emotional (V) and rational components (P) of decision-making. It treats them as separate modules, which could be added, multiplied or joined in some other way, although the base AZ model simply adds them.

The agent's total disposition (D) to act is given by the equations (6-1) – (6-3)

$$D^{total}(t) = V_i(t) + P_i\ (t) + S(t) \tag{6-1}$$

$$S_i(t) = \sum_{j \neq i} w_{ij}(t)[V_j(t) + P_j(t)] \tag{6-2}$$

$$\frac{dV_i}{dt} = \alpha\beta V_i^{\delta}(\lambda - V_i) + \alpha\beta(0 - V_i) \tag{6-3}$$

Where:

$D^{total}(t)$ - Disposition Score at time t

$V_i(t)$ - Emotive (or Affective) score of i^{th} agent at time t

$P_i\ (t)$ - Logical score for the i^{th} agent at time t

$S_i(t)$ - Social score of the i^{th} agent – based on other agents connected to this agent at time t

w_{ij} - Weight between i^{th} and j^{th} agent – normally 1

δ - set to zero in this simulation, but changes shape of RW function

λ - represents $Vmax$

$\alpha\beta$ - Represented as one factor in this simulation, but α represents the salience of the conditioned response (the Bell in Pavlov's experiments) and β the salience of the unconditioned stimulus (eg Food)

Epstein generalizes the RW model to permit *S*-curve learning and other variants. The first term of right hand side (RHS) equation (6-3) represents the generalised RW equation. The second term of the RHS represents an extinction component that

[153] Labels used by Epstein to represent such components.

eventually resets the V score to zero in the absence of any further stimuli.

Agents act when the disposition score D is above some trigger threshold. Scores range from [0,1]. The P or logical value in Epstein's agents are calculated by the relative frequencies of agents in the locality (defined by a visibility radius e.g. number of squares). In this thesis, formulation P is calculated using investment criteria e.g. revenues vs expectations.

The original Agent_Zero formulation uses a square grid as its environment. Extension of the grid to a more realistic environment would be an obvious next step. The formulation in this thesis effectively puts agents /customers at nodes in a social network. Epstein's model was also based on three agents; this model will be based on around 50,000 agents, so simple addition of V,P and S as presented in [89] could present unrealistic results.

Epstein and Chelen [429] in reviewing future directions and challenges with the model bring up the following important issues and potential ideas for future developments.

Issues with behaviour at scale; incorporating behaviours at scale; consideration of intra and inter-modular interactions (e.g. like cognitive interactions with emotions); using realistic geographies for agents, and consideration of homophily[154]. Epstein and Chelen also suggested the use of the temporal dimension model (e.g. Reinforcement Learning) as a replacement for the RW equation.

154 The tendency for people to have ties with people who are similar to themselves.

6.1.16 Summary of Modelling Environments for Human Behaviour in Social Settings

The software frameworks associated with base systems (note that not all the extensions associated with models like SOAR etc., are considered), are summarized in Table 6-1. Note because of ease of use, fast development times and libraries available to the author, Python has been chosen as the development language. The last column in the table provides comments/links to the Python versions of the software frameworks.

Approach/ System	**Description/ Overview**	**Programming Language**	**Python Version**
Clarion	Clarion is a cognitive architecture based on R Sun's "Anatomy of the Mind" [436]. Connectionist architecture used in cognitive social psychology using implicit and explicit representations of memory.[155]	C++	PyClarion. Not a full version. https://github.com/cmekik/pyClarion/blob/master/readme.md
SOAR	First used in 1983.Cognitive architecture providing building blocks for representing knowledge to realize the full range of cognitive capabilities found in humans, such as decision-making, problem solving, planning, and natural language understanding of different aspects of human behaviour.	C/C++ Visual SOAR to aid in easier development [437]	A minimum working example exists for using the SOAR cognitive architecture with Python. Creates an agent that interacts with the environment using SOAR's input-output links. https://github.com/KRaizer/Soar-Python-Minimum-Working-Example

[155] Implicit – type of memory that stores past experiences to aid and adjust performance. Explicit – knowledge that has been codified and stored.

Approach/ System	Description/ Overview	Programming Language	Python Version
Agent_Zero	Generative Framework developed to model Human Behaviour. Developed in 2014.	Netlogo	None. A Python [438] and Java [439] API exists to link to/from Netlogo. Netlogo simulation output can also be sent to R using this API [440], for further analysis. Equations representing an Agent Zero model can be easily coded in Python.
CONSTRUCT	For Organization modelling – Knowledge based on Norms. Could be very useful in modelling organizations in future work	C++, XML	Can create and extract XML data that can be passed to a Python model.
ACT-R	ACT-R (Adaptive Control of Thought – Rational) is a cognitive architecture based on the ACT theory for simulating and understanding human cognition. ACT-R is used to understand how people organize knowledge and produce intelligent behaviour. There was a connectionist (NN) version of ACT –R developed in 1993 [441]	Interpreter written in Common Lisp	Python ACT –R https://sites.google.com/site/pythonactr/ https://github.com/jakdot/pyactr There is also a lightweight version of ACT R called ACT UP[156] [442] and an associated Python version PyACTUp. https://pypi.org/project/pyactup/

Table 6-1: Summary of the main cognitive and emotional modelling platforms

6.1.17 Selecting an Appropriate Emotion/Social Framework?

There are many theories of emotion and social behaviour and just as many techniques with which to model them. In an ideal world, one would develop an agent that can act and think like a real human being and include cultural, emotional,

[156] Design to help make ACT R more scalable and uses less components.

cognitive functions, but these agents are likely to be computationally inefficient, especially when they are scaled, and at times would provide more functionality than required. Typically, detailed computational cognitive systems involve experiments with two to 10 agents at most, to reduce run times. ABM models tend to use simpler formulations so that simpler faster agents can be constructed with all the characteristics required to answer a particular research question. In the following sections the various cognitive and generative modelling frameworks that could be used within the thesis' ABM framework, are assessed using a needs analysis of the said systems against a set of goals for this thesis, resulting in the selection of an appropriate modelling framework.

Suitability of Existing Systems; Needs Analysis

Selection of an appropriate framework for this thesis, has been performed using a needs analysis like that presented in section 3.4.

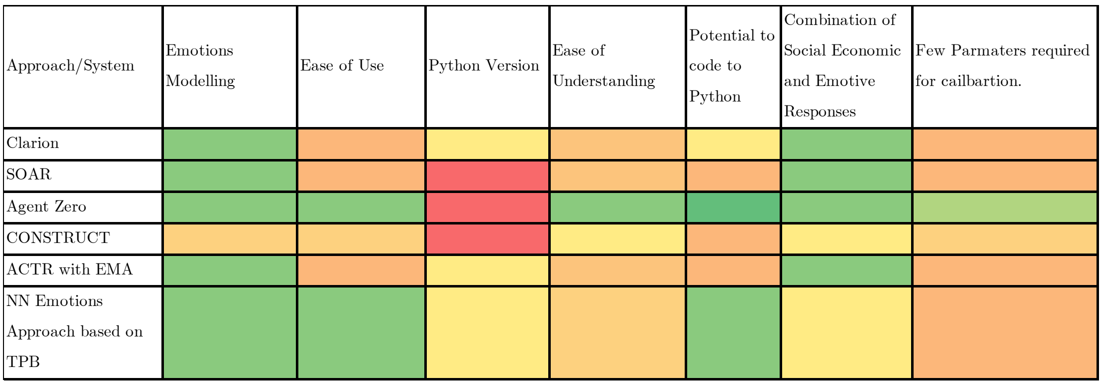

Figure 6-5: Modelling system fit to domain problem

Figure 6-5 compares the frameworks presented in Table 6-1 using selection criteria that place a heavy emphasis on, the ease of use, ability to model and whether it can be easily ported to Python[157]. Colours represent scores of 1-10 where dark green represent higher scores. Only the main cognitive models have been presented in this table rather than specific extensions dealing with emotional aspects (e.g. EMA with SOAR). As can be seen, the original Agent_Zero framework provides an easy to use, easy to describe and understandable framework, that was designed for ABM simulations albeit for small ones. It also has a simple cognitive/decision-making ability built in as well as a social dimension that can be easily used with a social network structure. Section 6.4 below describes the adaption of said Agent_Zero framework to fit with the needs of the simulations used in this thesis and described later in Chapter 7/8.

6.2 Representing Bidding in ABM agents

Agents in this simulation will be bidding flexibility into a power market, so there is a requirement for computational representation of this function and behaviour. There are a number of papers [20, 443-447] on implementations of software trading agents in "Silico".

Early work on the use of neural nets in financial modelling in artificial stock markets environments including trader formulations can be found in [448-451]. One of the first formulations of trader dynamics in a stock market trader environment is described in Bell Trotti Margarita and Turner in [448]. It uses neural nets to represent an agent that can hold cash or buy or sell shares.

[157] Python has been chosen as the language for development in this instance.

The Trading Agent Competition (TAC) was created in 2000 to provide an organized competition where agent design could be tested "free of the complexities and risks of operating in open, real-world environments" [452]. Over the years, the competition has been extended to other domains, including power, in the form of the Power TAC competition from 2009 [453-455].

An analysis of the competitions and reviews of winning models are typically published in literature after the event [452, 456-461]. Many different types of Agent have been used to trade in this competition and include constraint optimization, machine learning, uncertainty models, empirical game theory, and a blackboard architecture with an evaluator (see table 3 in [452]). The successful agents do not blindly follow price patterns but use a variety of information sources to outperform other agents.

Duffy sets out different agent learning types that provide bidding behaviours in an economic setting [462]. The paper provides a good review and comparison of these various types of trader agent and includes:

- Evolutionary algorithms
- Belief based learning
- Reinforcement learning agents
- ZIP adaptive type agents

Evolutionary algorithms typically use replicated dynamics, genetic algorithms, classifier systems and genetic programming and are based on biological principles of developments and natural selection. The genetic algorithm (GA) approach [463, 464], and (p120 -136 in[465]) is one of the few learning paradigms that allows for new strategies to be developed.

The belief based learning technique is the only type that uses beliefs about agents intentions and strategies to select its bids. Reinforcement Learning (RL) essentially uses or learns from historical patterns. RL has memory unlike the ZIP based systems. RL performs well in stationary environments but can take a relatively long time to converge.

6.2.1 Reinforcement Learning and Learning Automata

Learning automata (LA) [466-468], studied since 1960s, are simple, low-memory machines for improving the probability of reward in unknown environments. They belong to the class of machine learning algorithms known as Reinforcement Learning (RL) e.g. Q, R and SARSA learning [124]. The use of Reinforcement Learning (RL) in artificial intelligence has been discussed since the 1960's. It is used in software agents to help them take actions in an environment based on a reward function. Agents use a trial and error approach and adjust their actions using feedback from the environment. Descriptions of RL engines/algorithms and the approach in general, can be found in [124, 397, 469].

Research on LA led to the developments of modern reinforcement learning techniques. In particular, later research in RL's introduced the idea of Temporal Difference (TD)[158] as a learning method for RL's. TD learning is in part based on the psychology of animal learning and secondary reinforcers [470, 471]. In TD-learning,

[158] This is just one of three approaches in RL (others are dynamic programming and monte-carlo).

instead of just updating the value e.g. Q-value of the last step, it also updates the previous steps. Therefore it has a time dimension.

TD can use a discounting factor λ to make changes to predictions made further in the past smaller relative to changes nearer in time.

LA's are characterized as policy iterators[159]. Note Q/R learning RL engines are value iterators (see Fig 6 in [472] for a comparison). Note a good review of the use of different types of RL/LA engines within wireless networks is given in this paper.

6.2.2 Strategic Bidding with RL's in ABM

Since 2008 the Java based AMES power ABM [128, 129] has allowed researchers the ability to adjust generator bids using a Variant Roth Erev (VRE) reinforcement learning algorithm. Lincoln et al. [473], used both a Q learning and Roth Erev RL to simulate strategic bidding within a generator agent bidding against four other generator agents within a Python environment. The environment also included a more detail representation of the power grid using an AC OPF (PyPower). Interestingly, the more "simpler" Q learning approach provides the agents with better convergence and performance in this work.

Later work also using AMES with its VRE, uses many more generators and a IEEE 30 Bus System to simulate the system[474].

The RL or LA approach takes many ticks for it to converge and it is well known

[159] Policy is a mapping of an action to every possible state in the system. An optimal policy is that policy which maximizes the long term reward.

that in environments were the dynamics are not stationary, learning can be problematic. That is not to say that researchers should not use these techniques as a learning paradigm, because some corporate actors might use such technology to formulate their bids, but to recognize that this simulation is likely to be non-stationary[160]. Separate work by Arthur and Dutt [475, 476] indicates that simpler algorithms such as those based on learning automata might better reproduce actual human behaviour, than more sophisticated RL algorithms.

6.2.3 ZIP Trader

Dave cliff in 1996 developed the Zero intelligence Plus software (ZIP) trading agent[161] [19-21, 477-479] to emulate trading agents in silica. The first heuristic uses fewer parameters than the various adaptations of this model e.g. Zip 60 [19, 20]. However, it has been found to be a good representation of agents in trading markets. The latest version of Cliff's agent that uses Deep learning can apparently out-perform real human traders.

Other trading agents have been developed over the years including Sniper [480]; Zero Intelligence Constrained [481] and the Adaptive Aggressive agent [482]. In addition reinforcement learning engines [124, 483, 484] and Learning Automata [466-468, 485] could also be used.

ZIP traders have rarely been used in assessing bidding behaviours in the power domain, but one recent paper was found [486] that uses a ZIP trader to represent

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[160] Results in Chapter 7 show this.

[161] Dave Cliff developed a trading algorithm known as Zero Intelligence Plus (Zip) in the 1996 for use in agent-based simulations of trading markets.

household bidding in a DSR framework. The simulation in Chapter 7/8 uses Cliff's original Zip trader algorithm as it is easier to implement and easier to understand. Rather than just use clearing prices as the input to the ZIP trader algorithm, this simulation uses a combination of clearing price, and a target price (whichever is higher)[162]. The target price is dependent upon customer revenue or aggregator profit expectations. It is considered an appropriate algorithm especially for modelling domestic customers in this thesis. Although it could be argued that a RL engine may be a more appropriate algorithm for corporate actors, this thesis utilizes the Zip trader algorithm for aggregators bid adjustments. Although RL has been used to model strategic bidding behaviours for generators it was thought that Aggregators and certainly Domestic consumers would behave more like traders or bidders acting in a stock market environment. The ZIP trader algorithm was designed with this in mind.

6.2.4 Other Methodologies for Bidding

6.2.4.1 Naturalistic Decision Making (NDM) – Fast Decision Making

For some years, Klein [487] has been working on a notion he calls "Naturalistic Decision Making," (NDM) and he has created models that depict how people make decisions in difficult situations, especially in situations under great time constraints e.g. an airline pilot with engine failure or a grand master chess champion. This is useful analogy for those modelling systems, which have to respond very quickly to changing conditions. Note that fast and frugal heuristics [488, 489] is a similar and potentially competing approach. Essentially, Klein suggested a model, which was

[162] Clearing price alone did not produce an appropriate agent behaviour for bidding, so the model was modified.

based on pattern recognition where humans look for cues/patterns that suggest a behavioural response. Although the model has a pattern recognition element, Klein's recognition-primed decision (RPD) model representation of the NDM framework includes more than just a pattern recognition approach. This model could be applicable to many of our agents in our potential system, and could be a fruitful avenue for further research. Computational frameworks for RPD do exist but all are currently Java/C++ based [490, 491]. A simpler version just using pattern recognition based on the CLIPS rule based engine framework [492] may be a useful starting point. CLIPS was originally developed by NASA in C but there is a Python binding (Clipspy) that could be used to store rules based on clearing price patterns

No power based agent model (MAS or ABM) are currently using a NDM based action/learning model. Interestingly, Stacey [493] has developed a conceptual model that reflects the idea that decision making models change as uncertainty and complexity increases, and that eventually under the right conditions the decision making becomes chaotic. That is, humans/organizations use different decision-making models in times of different organizational stress. This implies that a model with numerous decision-making modes could be required, or at the very least, a model that can switch between these different modes.

6.2.4.2 PID Controller Approach to Human Behaviour: Setting Targets or Setpoints

Finally, Carrella uses a PID (Proportional Integrated and Derivative) controller to model the economic behaviour of human agents [494]. He calls this approach Zero-Knowledge Traders. Unsurprisingly, he shows that changing the relative speed of adjustment of production targets to prices generates completely different disequilibrium dynamics. An interesting idea, as essentially the agents use set-points to change their behaviour. As will be shown, a similar idea is used in the simulation discussed later, but using ZIP traders. The set-points are either customer expectations or aggregator profits in this instance. However, although the set point setting for aggregators proved to be much more involved than just setting targets at minimum profit levels. One of the key difficulties with this approach, however, is how to suitably fine tune the PID controller's parameters.

6.2.4.3 Deep Reinforcement Learning/Recurrent Neural Networks

Arlt [495] in her thesis on the economics of flexible loads proposed an economically motivated bidding function for HVAC systems that uses Deep Reinforcement Learning as a solution approach to determine effective demand response price[163].

Finally the authors in [496] developed an aggregate responsive load (ARL) agent which utilizes two Recurrent Neural Networks (RNNs) with Long Short-Term Memory units (LSTMs) to enable domestic users elements to collectively participate in the system.

An ARL agent in this architecture has the ability to submit bids that represent different houses and provide responses to the market-clearing price with a price dependent load. In this way, a single ARL agent behaves the same way as the transactive elements in hundreds or thousands of houses. The agent has been tested using a PyPower grid representation using GridLab-D [497]. The agent effectively learns bidding behaviour using Neural Nets. Both of these approaches represents an alternative approach to bidding and have been used to represent bidding behaviour in

[163] Note Dave cliffs latest version of ZIP trader uses deep reinforcement learning.

PNNL's Transactive Energy Co-Simulation Platform (TESP) [496, 497].

6.2.4.4 Summary of Bidding Approaches

Although any or a combination of the techniques discussed above could be used to adjust bids, for ease of use, computational complexity and understanding Cliffs ZIP Trader algorithm has been used to adjust both Aggregator and Customers bids in the work discussed in chapter 7/8. Future work may consider RL or LA algorithms.

6.3 Graph Theory, Networks and Social Network Modelling

Power networks, as well as social networks, can be represented as a connected graph. Mathematical techniques can be applied to analyse such representations to derive statistics of particular graphs like shortest path length, clustering density and so on. Key nodes and cliques can be found, and propagation analysis can be performed. Furthermore, network analysis is essentially applied graph theory. For a good introduction to network analysis the reader is referred to texts [498, 499], while a brief history of network modelling is provided in Chapter 1-2 of [500].

In addition, it is recommended that the following texts should be read for an introduction to small worlds [188] and for a discussion on weak links, fractals, scale free networks and pink noise [501].

Finally, networks can be represented in matrix form as an adjacency matrix. It is a square matrix used to represent a finite graph. The elements of the matrix indicate whether pairs of vertices are adjacent or not in the graph. Power networks, small world networks/social networks have sparse adjacency matrices, and thus sparse matrix multiplication can be used to efficiently represent the adjacency matrices, as well simulate propagation in a social network. Considering that, the software implementation of this thesis is in Python, the open source library for sparse matrix creation and manipulation Scipy.Sparse, has been used.

6.3.1 Network Computer Modelling Libraries

There are many open source computer packages available, both to generate networks and to provide network analysis algorithms, to calculate statistics or highlight propagation dynamics. In Python, NetworkX [502, 503] is the most pervasive of libraries used of all. For example, SmartNet/PyPower uses NetworkX to represent power network topology and flows.

SNAP [504, 505], is large-scale, low-memory usage system that provides an easy to use commands for the analysis and manipulation of large networks. It was also designed to analyse large social networks. Table 6-2 summarizes the main open-source network packages available to analysts for coding.

Name of Modelling Library	**Overview**	**Advantages**	**Disadvantages**
Network X	Python package for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks.	Used extensively in power models in Python e.g. SmartNet, PyPower. Easy to convert network format to adjacency networks – command available. Converting NetworkX to adjacency matrices is easy. Considered more flexible than SNAP - [506].	Slower than SNAP [506].

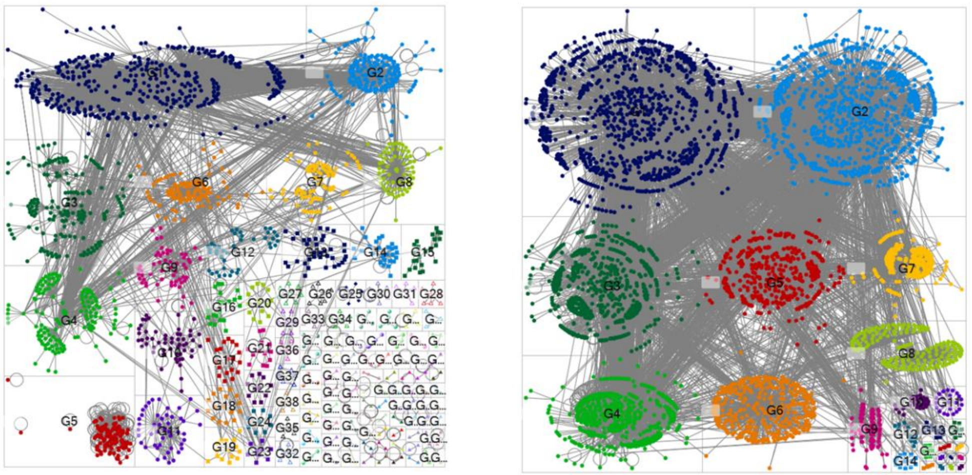
Name of Modelling Library	Overview	Advantages	Disadvantages
igraph	A collection of network tools with emphasis on efficiency.	Easy to use. C library with Python interface. Faster than NetworkX.	10-20% slower than SNAP.
NetworKit	A growing open-source toolkit for large-scale network analysis.	C++ with Python interface. Fastest of all. However, speed reduces as problem size becomes very large. Can be 1.5 - 4 times faster than SNAP.	Not easy to use – less well supported.
SNAP	Stanford Network Analysis Project. C++ network program that scales to massive networks with hundreds of millions of nodes, and billions of edges. It efficiently manipulates large graphs and can analyse them.	Large-scale. Fastest system. Well supported with many data libraries available for social settings. Very fast loading of saved networks. Written in C++ but with Python interface. Also has Excel based Network modelling environment - NodeXL. "SNAP runs 1 to 2 orders of magnitude faster than network X. SNAP also uses 50 times less memory"[506]. NodeXL uses SNAP algorithms to perform calculations. NodeXL is very easy to use especially for "small" (5,000 node) networks. One click plotting available in this package.	Less user friendly than NetworkX.

Table 6-2: Summary of open-source network packages

Experimentation with the various packages (with SNAP and NetworkX in particular) on a large network of ~50,000 Nodes shows that SNAP provides the fastest response. Because the network that is modelled in this thesis consists of 50,000+ customers represented as a social network, SNAP was chosen as the modelling environment for social networks. Test Networks for social patterns based on interactions in Facebook and Twitter are also readily available in the SNAP framework and available for download.

6.3.2 Analysis of Test Social Networks (Facebook and Twitter)

Using samples of Facebook and Twitter networks, analysis of these networks using NodeXL[164] [507-509] indicates that the two systems have quite distinct shapes, as illustrated in Figure 6-6, and as a result, network propagation dynamics would be different. In the context of this thesis, these network cases provide scenarios for testing social network interactions to understand the extent of their impact on power system operation.



(a) Sample of 5000 nodes in Twitter Network *(b) Sample of 5000 nodes in Facebook Network*

Figure 6-6: Social network structure comparisons: Accessed from NodeXL/SNAP datasets 20/12/18

Analysis of the node degree frequency of links (known as Degree K) in the networks

[164] Note NodeXL software is based on SNAP.

shows that this difference comes about by slight differences in the frequency of connecting nodes as shown in Figure 6-7.

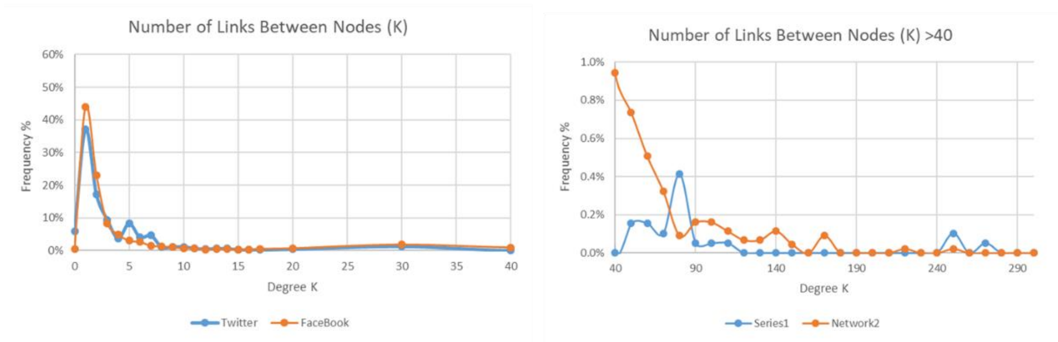


Figure 6-7: Frequency analysis of node degrees for two network types

From the above, comparison/analysis of these social network cases show that small differences in node connection probability can have significant effect on the structure of social interactions.

Node connection probability distributions like those in Figure 6-7 can be used to synthetically generate network structures. Barabisi [510] proposed attachment probability distributions to create synthetic interaction networks for later analysis.

Chappin and Afman used such a generator approach to generate small world networks to test out the diffusion of LED light bulb technologies in an ABM simulations of consumers [511]. Many network modelling libraries also exist that can easily allow synthetic networks to be created. NetworkX [502, 503] models around 1300 of the graphs listed in Reads' Atlas of graphs [512, 513]. Brinkmann et al also provide a useful database for searching for different types of networks [514]. Use of such generic graph generators provides a mechanism to test out the effects of many different social network configurations on the dynamics of a simulation. This thesis will focus on the two social networks above and a theoretical small world network, but future work would make use of additional network structures to widen the scope of the study. Simulations with and without social networks are given to compare the effects of including social network effects in power simulations.

6.4 Adapting Agent_Zero to Represent Power Customers interacting with Aggregators

Section 6.1.15 introduced the concept of Agent_Zero and equations (6-1) - (6-3) set out the formulae for calculating the agents "disposition to act" and "emotive scores". The original Agent_Zero framework was designed to operate on a 2D grid with a maximum of three agents and will need to be adapted to operate in a more complex environment as detailed in this thesis. The modifications to the agent zero framework are therefore described in the sections below.

6.4.1 Logic (P Score)

Unfortunately, the Agent Zero (AZ) framework in its current form does not provide us with a reasonable way to consider the economics of a contract offer in a power aggregator simulation[165].

The logical component P in the original AZ model uses a simple count of nearby neighbours to calculate a score for its logic component. In our case, a value based on the economic assessment of the aggregators performance would be more appropriate – e.g. revenues, NPV or some other economic measure. Therefore, a method must be

[165] Aggregators offer new contract terms that customers will need to evaluate.

developed to normalize an economic score into an Agent_Zero framework. Agent _Zero currently uses scores ranging from zero to one. Profit or NPV assessment, usually used in economics would provide an assessment that would be far greater than one e.g. £10.7 million profit per year and may even be negative. Some transformation function e.g. like a sigmoid function will be required to convert profits into a [-1,+1] score. The general logistic equation has been chosen as the transformation function to convert customer revenues to a normalized value of [-1,+1]. The generalized logistic equation can be used to represent a multitude of functions but the sigmoid or S curve function has been used. Many natural processes, such as crop yields, learning curves, and economic growth exhibit an S curve shape. It is likely that utility associated with revenues from flexibility provision would also follow an S curve type relationship. Of course, with the appropriate data, curves could be calibrated, but this data is not currently available.

6.4.2 V- Emotive Score

The V[166] or emotive score "accumulator"[167] approach does provide us with a reasonable way to represent an emotional score e.g. "I do not like this aggregator". However, the original Agent_Zero framework only used one accumulator to represent emotions, whereas this thesis proposes the use of N accumulators representing the

[166] Agent_Zero uses V for emotions, P for Logic and S for social interactions (see 6.1.15). It might be more appropriate to use E L and S instead, but the thesis sticks with the original Agent_Zero formulation.

[167] Accumulator – The emotive score builds up over time, with some degradation or leakage and can be compared to filling up a tank or an "accumulator".

emotive scores associated with the N aggregators that the customer is considering.

This fits more closely with the computational biology approaches using accumulator model dynamics[168] [515-518] to represent decision choices; here multiple accumulators are used (accumulator model dynamics) to keep track of scores on perceptions associated with various stimuli. Accumulators can have leaky components be non-linear and have inhibitory functions where one accumulator can lockout another.[169]

6.4.3 Message Fatigue

In the case of social interactions, it is recognized that bombardment of a message repeatedly could result in message fatigue[170]. This is acceptable for the three agent model presented in [89], but could present a problem in a 50,000 agent simulation. The Weber model [519-521] provides a useful solution to this problem.

In the Webber model, the result of a stimulus is considered to be a function of log (S1/S2)[171] - so it gets progressively harder to move the "dial on an issue", the higher the score. For example, I have heard the rumour 100 times already; hearing it two or three times more would not change my opinion too much but hearing it, 100 times more might.

Although the addition of a Weber function to the current model might be useful,

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[168] Note the accumulators are represented as integrated linear or non-linear functions.

[169] Note in this work only the leaky component is modelled. Accumulators do not lock out other accumulators.

[170] Where overexposure to the same message can result in avoidance, annoyance and desensitization.

[171] Where S1 is the current stimulus and S2 is the cumulative stimulus so far.

it was found this was less of an issue in the current simulation than thought. Note that the simulation results show that the propagation of messages typically only amount to five messages per week per customer on average[172]. This is because there are few connections between most of the customers. Thus, overloading of agents with messages does not occur. In addition, the RW model to some degree reduces the effect of each stimuli as it looks at the difference between the current and the max emotive score[173] i.e. (1-V_i).

6.4.4 The Dynamics of Agent_Zero

Although AZ can be considered a "simple" model, it provides interesting social dynamics in its simulations. As various case studies in [89] show, agents can hold very firm logical views about an issue but social pressures can drive a collective behaviour which goes against these staunch logical views. In the context of this thesis, behaviours, such as this, might be expected:

Customer 1 prefers on an economic basis to pick aggregator company 1. The customer agent is connected to 20 other agents who are all strongly against Aggregator 1. They have bad experiences with the aggregator. Over time, it might be expected that Customer 1 would change its mind and select a different, less economically attractive, aggregator[174] if social pressures are strong enough. Chapter 8 will show that this is exactly what happens with the Agent_Zero formulation.

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[172] From inspection of the simulation results.

[173] Max emotive score set to one in this model.

[174] Note this does occur in the simulation.

6.4.5 Multiple and Mixed Emotive Scores.

The original AZ framework uses one RW emotive accumulator to keep track of an emotion score V, takes P values (logic) from data surrounding the agent in a 2D grid and takes dispositional scores, D, from nearby agents to form an average score S [89]. However agents in this simulation will need to keep emotive scores of many aggregators (e.g. six), as well as keep account of angry stimuli and happy stimuli from many connected customers via a social network. The agent, therefore, needs "multiple Agent_Zero's" inside of it, each accounting D,V, S and P scores for each aggregator. This is the structure that has been used in this thesis and is shown in Figure 6-8.

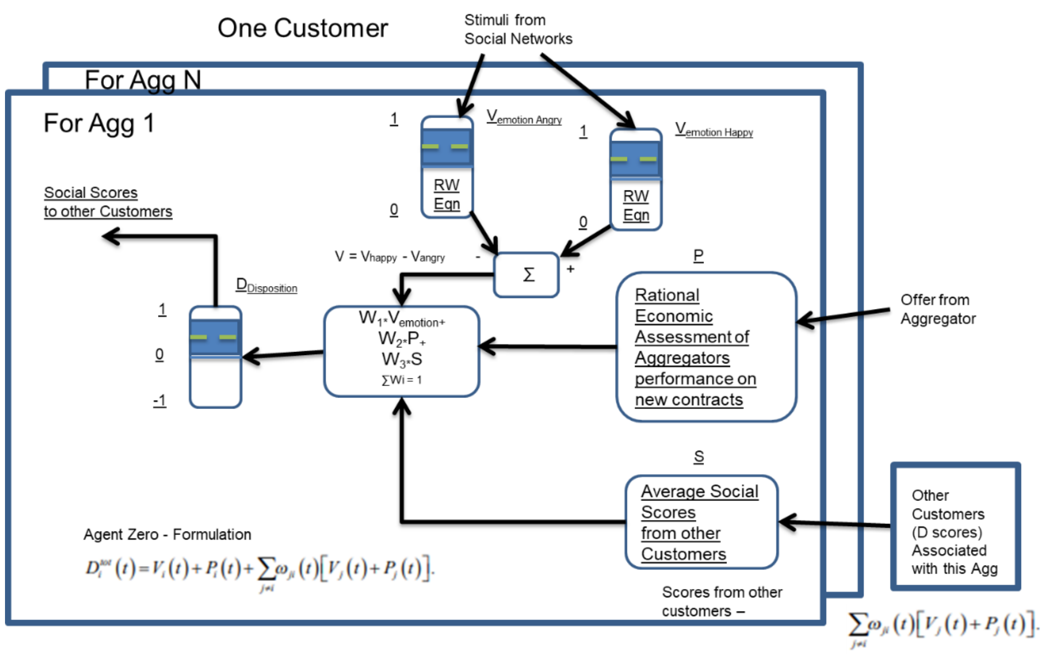

Figure 6-8: Customer Agent_Zero framework; Multiple accumulators for aggregator assessments

Therefore Customer agents compare D values to assess aggregators overall performance and take action to change aggregator contracts based on this comparison shown in Figure 6-9. Most conventional models would perform this comparison on a rational or economic basis, but in reality, domestic customers are likely to perform this using a number of inputs including from their friends, their feelings and logic. Of course, some customers would be entirely logical while some would rely solely on their friends or family's opinions. The AZ framework allows the incorporation of all these elements in a relatively simple and understandable way, by changing the relative weightings of the V(emotional), S(social) and P(rational/economic) scores in the agent calculation.

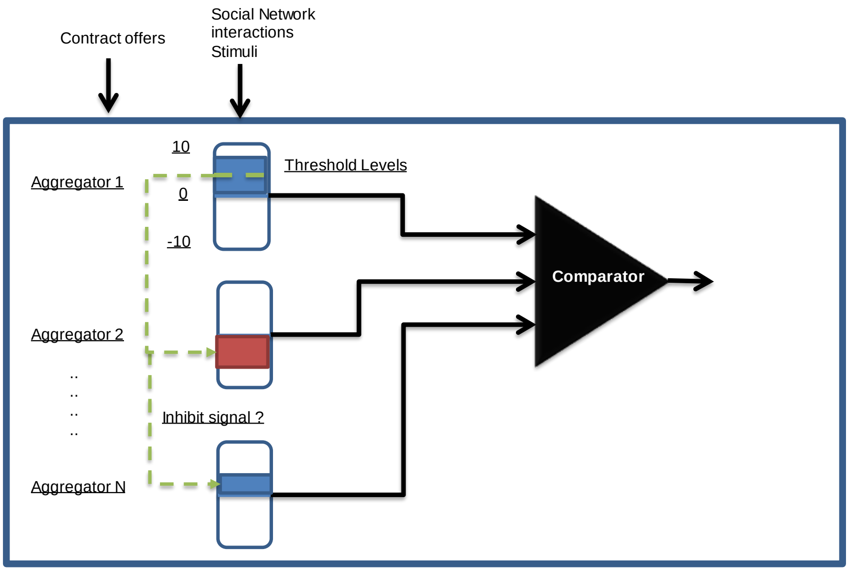

Figure 6-9: Customer Agent_Zero decision framework; Choosing an aggregator contract

6.4.6 Evolution of Agent_Zero Scores: A Hypothetical Example

Using a simple random input stimulus sequence across a number of weekly ticks, a number of cases have been simulated using the equations in section 6.1.15 and are shown for four hypothetical cases below[175]. The simulations are for one simple agent_zero module as set out in section 6.1.15. P and S score have been provided as inputs and varied to show the impact on the Agent_zero calculations.

Figure 6-10 shows how the emotive score (V) from the RW model[176] increases and declines with and without stimuli. Values for V and the stimuli inputs range from [0,1]. Note that the strength of the stimulus and frequency has an impact on the rise of V as shown in Figure 6-10.

[175] An Excel based simulator was used to generate random inputs and provided the resulting hypothetical outputs. It was also used to help verify output from the Agent Zero modules in the main model discussed in chapter 7.

[176] With extinction decay.

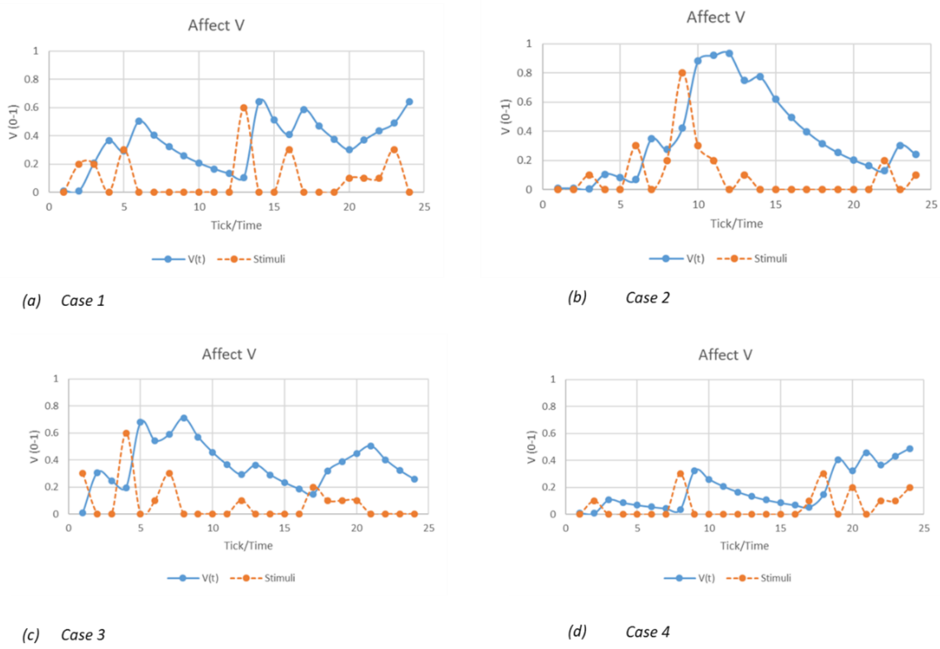

Figure 6-10: Example of emotive score (V) evolution

Without stimuli, the RW with decay model will eventually decline to zero, dependent upon the values of alpha and beta in Equation (6-3) (2nd part RHS). The simulation framework developed in Chapter 7 allows the user to alter the sensitivity of the messages on the RW model e.g. five messages might be required to be the equivalent of a 1 value stimuli.

The P and S scores are at discrete points e.g. at tick 7 and 15 in the hypothetical curves shown in Figure 6-11. The P and the S scores in this hypothetical model are supplied as inputs, as only one hypothetical agent is being simulated.

Figure 6-11: Example of Agent_Zero scores (D,V,S,P) evolution

Figure 6.11 shows how the D score could vary depending on input stimuli and the view of the economics (normalized P score) and the impact from connected agents i.e. the S score. The S score in the actual model discussed in chapter 7 is derived from a calculation using the social network represented as a sparse matrix. This makes the computation very fast. In the actual model, S is simply the average of all D scores of all connected agents and a different S is calculated for each aggregator. The D score in Figure 6.11 above is just a simple average of V, P, and S shown in the figure.

6.4.7 Averaging V, S, and P, or Rule Based: Which One to Use ?

The current incarnation of AZ in this simulation uses a simple weighted average of the S, P and the V scores. The base case uses the same weights for the three scores, set at 1/3, and therefore produces an average value. Sensitivities around this have been performed. The question is; is a simple weighted average model of V, S and P, an appropriate representation of the human behaviour? For example, would it be appropriate to average say a V score of -0.3 with an S score of 0.4 and a P of -0.1. The average score would be zero. Would it be more appropriate to recognize that the S and V score (feelings and social score nearly cancel each other out) and therefore P should have a greater impact on the score. Alternatively, should some other rule be used? For example, if P greater than 0.7 D=P and so on. A fuzzy rule based system might also be more appropriate but this will not be investigated here. Future work might incorporate survey results from real customers to help shape the formulation of the weights and or potential rules.

6.4.8 Discussion

There are many theoretical constructs that could be used to model behaviours or emotions in particular. To discuss behaviours it is important to understand in what context the problem domain fits. Human behaviour is closely tied to rationality, social influence and finally social structure. The key question for researchers is which of these aspects is more important or is it better to consider combinations of various modelling constructs?

In an ideal more realistic simulation of behaviours, one might consider interactions between cognitive functions, emotions, and personality. Co-evolution of those aspects might also be important. This might provide a more accurate representation but at the expense of computational complexity.

In terms of the AZ framework, model parameters like alpha, beta, the decay factor, the weights for V, S and P, and the scoring function (i.e. the general logistic equation parameters) will need to be set. Data driven/machine-learning approaches would be helpful in this regard, but machine-learning algorithms can only capture relationships that they have seen before. Currently, no data exists on the operation of a low carbon flexibility market with domestic customer participation at scale.

Cultural and other factors such as affluence, technological affinity would all impact on cognitive ability and emotional response. The current simulation does not take account of this.

In the meantime, the use of a parameter sweep/sensitivity approach to gauge the impact of the AZ framework on simulations seems like a reasonable one.

6.5 Chapter Summary

Future distribution flexibility systems will require the participation of new actors like domestic customers and aggregators. The behaviour of these actors will impact on DSO operation and their longer term planning and will impact on Regulator's market designs. Current tools do not adequately represent human behaviour in their models. A tool implementing human behaviour is therefore essential if appropriate designs are to be formulated. Therefore, this is an important chapter as its sets out a contribution to the state of the art in modelling flexibility markets by using an extension of the Agent_Zero approach using multiple accumulators to model social logical and emotive behaviour.

This chapter considered many computational systems for representing human behaviour and has opted to use the Agent_Zero (AZ) methodology as an easy to use and understandable framework that provides researchers a way to represent customers in an aggregator flexibility market. This framework uses social, logical (rational/cognitive) and emotive (affective) elements to represent human behaviour whereas many other methodologies focus on one or two of these elements[177]. The framework has been extended to include multiple emotive modules (angry/happy and for multiple aggregators) and includes the economics of customers contracts with normalized scores using a generalized logistic equation. Social networks have been introduced as a methodology to propagate messages between customers and allows the AZ framework to be expanded from a 2D grid environment. The network that will be used in this network is synthetic, as customers have been randomly distributed on a large network. With the appropriate data, a more realistic distribution of agents may have been effected.

The next chapter sets out the design of agent based modelling system in Python that uses the work discussed in Chapters 3 - 6. This ABM framework forms the basis of the simulation results presented in Chapter 8.

[177] Admittedly, sometimes-in more detail.

Chapter 7

A Power Based ABM Simulation Framework with Human and Corporate Behaviours

The research on the UK Balancing Market (Ch 2), business models, costs and associated aggregator economics (Ch 4), risk management (Ch 5), and the Agent Zero framework (Ch 6) to represent emotions and social interactions, is brought together in this chapter to construct a new and innovative ABM modelling environment. The tool that is presented in this Chapter provides six distinct contributions to the state of the art:

1. It is first application of an extensible Python based ABM framework that includes the interactions between customers, competing aggregators (six) and independent system operators in a power domain setting.
2. Includes corporate aggregator's business models in the context of a future wholesale flexibility/balancing power market. Aggregators can change Business Models throughout the simulation.
3. It includes corporate actors using risk management techniques and utilizes an exotic three-asset Monte-Carlo based real option approach to represent risk in a power aggregation market.
4. It allows aggregators to adjust and bid for new customers on a monthly basis.
5. It incorporates a large social gossiping network that is used to affect emotions

and provide a social network dimension to customer's emotions.

6. The tool uses a novel extension of the Agent_Zero framework to model emotions, economics and social impacts. When social networks are combined, the Agent Zero framework provides social interactions that influence aggregator choice. Behaviours are seen that are not evident in other system designs. It thus provides a novel tool for implementing human behaviour in a market with millions of participants e.g. Domestic customers. This is an important principal contribution to the state of the art in modelling flexibility markets.

This modelling framework known as PyEMLab-Agg, is based on the EMLab model (Ch 3), built in Java. EMLab focuses on simulating the design of policies for transmission assets and simulates the introduction of new generation technologies and their impacts. It models commodity and CO2 markets and includes the German and Dutch transmission grid as a two-node network. EMLab has been ported to Python (PyEMLab) by the thesis author and additional new agents discussed below have been introduced to the framework.

The Python object-orientated PyEMLab-Agg model has been developed to simulate a low-carbon distribution network where customers provide flexibility via a bidding market, managed using aggregators and an ISO. The effect of corporate behaviour (aggregator companies with risk management) and more human like customers (emotional and bidding behaviours using a modified Agent_Zero framework) have been included to provide a more holistic view of how this market might operate in the future and have been used to generate a number of scenarios.

In this model, individual households (Domestic Customers), small and medium sized entities (Industrial Customers), aggregator companies, generators and the Independent System Operator (ISO) are represented as new agents (see table 7.1 below).

Agent Type	Domestic Customer	Industrial Customer	Generators	Aggregator	ISO
Description	50000 Domestic customers (see Note 1) with an average domestic load of 4000kWh/yr + EV 's and Solar panels etc. as appropriate	4500 Industrial customers /SME's (See Note 2). Average load 35,000kWh/yr	57 Generators with bidding characteristics of conventional generators e.g. CCGT, Hydro, diesel etc.	6 aggregators initially with ~ 8333 Domestic customers and 750 Industrial customers	One ISO accepting bids from generators and aggregators. Economic Dispatch
Roles	Submit bid to Agg	Submit bid to Agg	Submit bids to ISO	Aggregate bids	Clearing
	Update Accounts (Revenues)	Update Accounts (Revenues)	Update Accounts (Revenues)	Submit bids to ISO	
	Update bid (Zip Trader)		Update bid (optional)	Disaggregate	
	Update Agent Zero			Update Accounts (Revenues)	
	Review Agg Contract Offers at end of contract			Update bid (Zip Trader)	
	Select New contract using AZ D scores			Adjust contract terms monthly for new contract offers	
	Propagate social media messages			Review performance yearly - Select New Business Model	
				Forecast and Analyse CP	
				Enter market	
				Exit market	
				Risk manage (options calculations hedge)	
				Update aggregator costs based on BM and customer numbers	
				Set targets for Zip Trader	

Table 7-1: Agent types and roles

Note 1: Using the analysis shown in section 4.3 it is clear that around 6,000 – 10,000 domestic customers are required for an aggregator to breakeven, depending upon assumptions. A competitive market will require 5-6 aggregator entities to meet competition requirements. Assuming 8000 customers per aggregator would therefore suggest that for a simulation to represent a competitive market of at least 40,000 - 48,000 customers would be required. In this instance, 50,000 domestic customers were selected.

Note 2: Dundee, a city which has around 50,000 Domestic households, is associated with around 4500 SME's (Scottish Government statistics).

Emergent phenomena are expected to be seen in this model, as it is a complex simulation that includes adaptive behaviour with emotions, competition amongst a set of aggregators for customers and bidding behaviour. Agents adapt to changing prices and offers made to them by aggregator agents. "Gossiping" over social media in the form of a network is represented and is used to transport messages to/from connected domestic customer agents providing additional dynamics to the simulation.

Section 2.7.3 has already set out the interactions of this model in the form of a story-board, so this section will focus mainly of the design and key components of the ABM model that has been developed as part of this thesis.

Section 7.1 will discuss then PyEMLab/PyEMLab–Agg framework in more detail. Section 7.2 will detail the design of the Aggregator agents and specifically their interactions with all the other key agents in this simulation, while sections 7.3 - 7.6 provide design details on other key agents i.e. the ISO, domestic and industrial customers, and generators.

Section 7.7 will present the approaches used to validate and verify the simulation framework. Finally, section 7.8 will discuss possible extensions to the model in future work. The structure of this chapter is summarised in Figure 7.1.

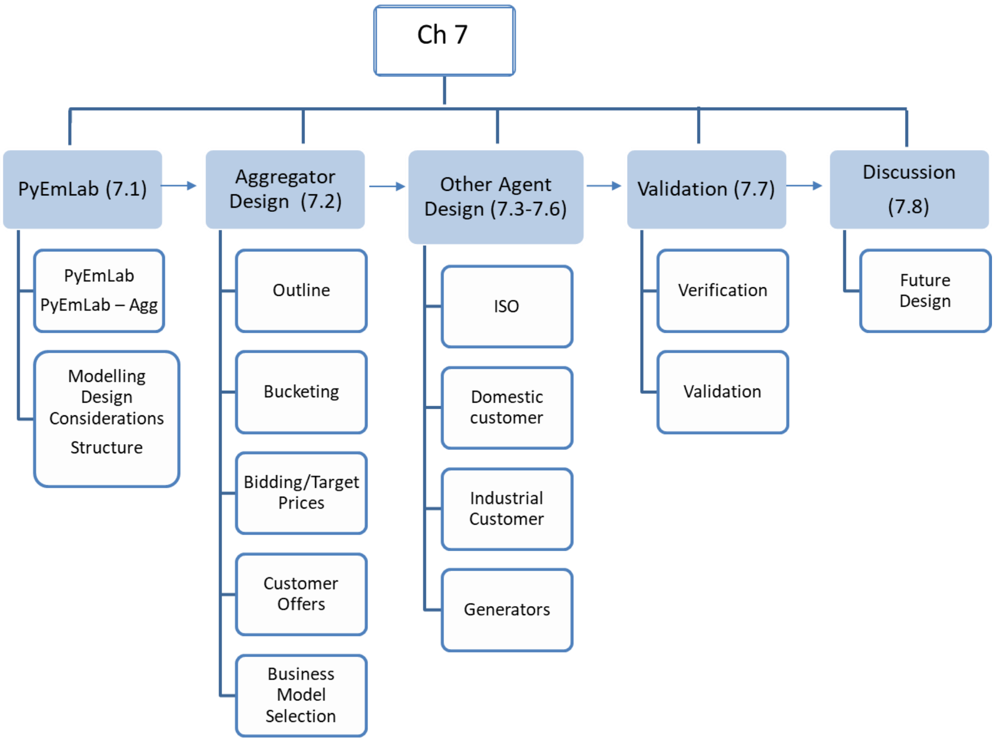

Figure 7-1: Overview of Chapter 7

7.1 PyEMLab: A Python based ABM Power Simulator

As discussed in section 3.2, there are only around four electricity/power-focussed systems available for power based ABM analysis and all are Java based [32]. EMLab[178] has been chosen as the framework in which to conduct the simulations for this thesis. Python as discussed previously, is easier to develop in, and is the language of choice now in the wider research community and provides the researcher with many simulation components not available in the Java environment e.g. PyPower, SmartNet and many other open source libraries. PyEMLab is a direct Python port of the EMLab

[178] EMLab is also Java based.

framework and PyEMLab–Agg expands the PyEMLab framework to include aggregators, social interactions ("gossiping"), human behavioural characteristics (Agent_Zero). EMLab focuses on policy decisions with generation technologies and its impact on prices and carbon emissions whilst, PyEMLab-Agg concentrates on flexibility market interactions within distributions systems.

Conversion of EMLab to PyEMLab

Using an open source "Java to Python" library [522] the Java based EMLab model was converted to its first form of the Python model named PyEMLab. EMLab makes extensive use of the Java streams concept [523][179], so PyEMLab utilises the Python equivalent "lazy-streams" [524]. As far as it is known, this is the first and only, fully Python based ABM power simulator currently in existence[180]. It will enable many more researchers (Python based) to experiment and extend power based modelling in an ABM environment, including with this work.

The first "port" of the code – proved to be slow for bigger simulations with a simulation of 20 years of 600 power plants taking some 20 mins. Code bottlenecks were identified[181] and further experimentation with the use of a Numpy and Xarrays (which is vectorization based) indicated that runs times of this same simulation could be reduced to around 15 secs. The current version of PyEMLab does not use lazy-

[179] Java Streams processes lists (or streams of data) and is ideal for processing collections or lists of agents.

[180] There are Java based simulators that provide users with Python Wrappers so they can run the Java model from Python.

[181] Streams processing caused many of these delays.

streams but utilises a much faster Numpy based system instead.

<u>*Extension of PyEMLab*</u>:

The original EMLab model assumed fixed demand using a 20-point load duration curve to represent demand over the year of two power nodes, Germany and the Netherlands. Extension of the model to include a networked power-grid, would allow modelling of nodal prices as well as to investigate congestion in the transmission network.

PowerGama, a European wide LP based power grid modelling tool in Python, would be an ideal extension to the EMLab environment [28]. It can be used to model congestion and associated investment upgrades to transmission networks. Experimentation with the PowerGama model has shown it can be linked to PyEMLab to interchange data i.e. nodal prices in PowerGama affect behaviour in the PyEMLab model and vice versa. Thus, as new generating units are added or old units are dismantled in PyEMLab, the underlying network representation within PowerGama is modified to reflect that change. In addition, the Python aggregator and distribution models in SmartNet could be added, since DSR or, more importantly, aggregation and flexibility markets are not represented in the EMLab model as demand is fixed by scenario input data.

7.1.1 "PyEMLab-Agg": A Model of Aggregators and Customer Interactions

The structure of EMLab/PyEMLab allows for the easy introduction of additional agents and provides an ideal and structured environment in which to model the agents and their interactions outlined in Chapters 3-6.

The agent types that have been added to the system and form the principal agents in this simulation are shown in Table 7-1 above, along with their key roles.[182] The agent based model presented herein is also described in accordance with the ODD (Overview, Design concepts, and Details) protocol [525-528] in Appendix J, while this chapter focusses on specific design mechanics of the system and its key agents. Note that the Generator agents in PyEMLab/PyEMLab-Agg refer to both large traditional and smaller distributed generators. In addition, PyEMLab-Agg includes Domestic Customer agents with solar PV, small wind turbines and EV's in their portfolio. The market clearing mechanism used in EMLab has been re-written so that it can accommodate an array vectorization approach[183] [529] and in future work an AC OPF simulation of network flows will be added.

Figure 7-2 summarises the key components and their interactions in the PyEMLab/PyEMLab-Agg framework[184].

[182] Domestic Customer, Industrial Customer, Generator, Aggregator and ISO agents. Roles define what an agent can do during the simulation.

[183] Vectorization is the process of converting an algorithm from operating on a single value at a time to operating on a set of values (vector) at one time.

[184] PyEMLab-Agg is the modified version of PyEMLab that is used in this simulation. Note it uses different agent types and roles from those uses in the base PyEMLab/EMLab model, e.g. additional Generator agents, Domestic and Industrial customers, a modified ISO and Aggregators.

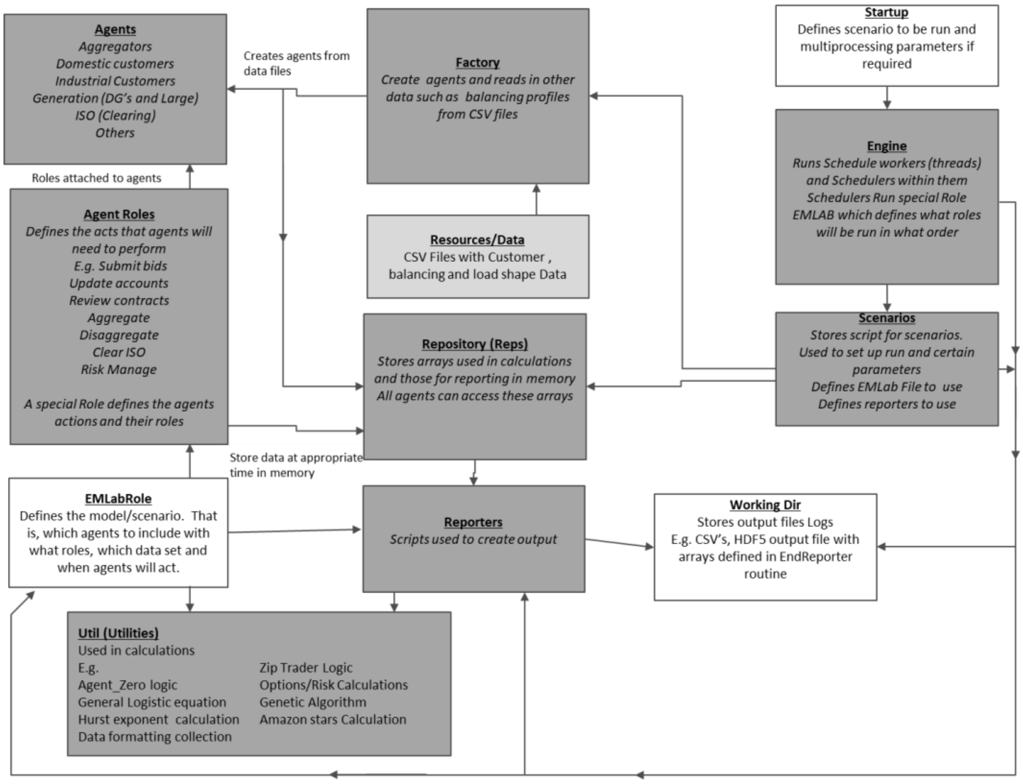

Figure 7-2: Key modules and structure in PyEMLab-Agg

Agents in ABM's normally have an "act" or "execute" method that is used by a scheduler to "kick off" actions inside the agent. The agents in Table 7-1 inherit that act code from the AbstractAgent in the gen.engine package in PyEMLab. PyEMLab performs "acting" in a slightly different way. Roles (agent behaviours or "things to do") can be attached to agents, via a scripting language defined in the EMLabRole module. The EMLabRole is a special form of role in that it defines what the simulation should do. This allows the user of this framework to attach different learning paradigms, e.g. ZIP trader vs a Reinforcement learning engine using one line of scripting code. In addition, different roles could also be assigned in the agent factories during agent setup, e.g. 30% of the customer agents could update their bids using RL, whereas the rest could bid randomly. Python scenario files are used to define simulation settings and set up agents using data stored in multiple CSV files and agent factories[185] (ch6 in [530]). Role files are stored in the package "gen.role" and there can be multiple versions of a role. In addition, agents can contain multiple roles.

Simulation runs are initiated by running a "startup" module stored in the engine package, which defines the scenario file to be used amongst other things. This file name is loaded dynamically, provides parameter settings, loads, and builds a simulation environment using parameters stored in the file. Agent and data "factories" are set in the scenario file and are used to create agents of different types, read in from a CSV input file. The scenario file uses an easy to use Python script that can be used to create any number of different scenarios. The "startup" file also defines which reporters[186] to use; reporters are used for reporting output data either during the simulation or at the end[187]. It also defines the mainrole class (typically called EMLabRole in this simulation). The mainrole is a script that defines the functions that are to be carried out in the simulation. That is, the process that the agents must follow. Finally, "startup" creates schedule-worker threads, which are used to run the main part of the model. Note currently the model is run with just one thread. The schedule-workers attach a scheduler to them that keeps track of the hours, days, week's months and years and sets appropriate flags e.g. the week_flag. These flags are used by agents to "kick off" appropriate actions like social media propagation etc. during the simulation.

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[185] Also sometimes known as Agent Builders, or creators.

[186] Reporters are Python script files that define what data is output where and when.

[187] The original EMLab model wrote data at the end of the simulation to a CSV file. This has been extended to include other file types and allows data writing throughout the simulation.

The scheduler launches an "EndReporter" class at the end of the run, saving the necessary data after the simulation is complete. The script in the "mainrole" file is executed once each tick (simulated hour) and specifies when and what the agents do. Because the "mainrole" is defined by name, researchers are free to store and use numerous versions of the this file e.g. mainrole1, mainrole2 etc. CSV and other data files are stored in the resources directory and are used to populate customer[188], aggregator data[189] and provide imbalance volume profiles to the model.

The utility package contains code segments that are used within the "mainrole" code, and sub-roles inside agents. Typical routines stored in here, include, risk management routines; option pricing; Agent_Zero algorithms, Hurst coefficient calculations and so on.

During the run, agent data is stored in a repository which stores in-memory matrices of simulation output like: clearing prices; flexibility volumes; contract offers; profit and loss accounts for both customers and aggregators; Agent_Zero values for each customers (V,S,P D)[190]; the number and type of customers by aggregator; key agent statistics and so on.

The original EMLab framework (and its Python port PyEMLab) was designed to simulate investment and technology behaviour in a European power market and its agents and associated roles are not appropriate for this current work. New agents/roles have therefore been constructed and this version of the model is known as "PyEMLab-

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[188] For example, max customer flexibility volumes, starting contract types and so on.

[189] For example, Risk stance, opening contract types and business model used.

[190] V – affective, S – social, P – logical score and D – disposition values.

Agg". Figure 7-3 provides a block diagram model of the PyEMLab-Agg framework, whereas Figure 7-4 provides a slightly more detailed breakdown of the interactions between the various modules.

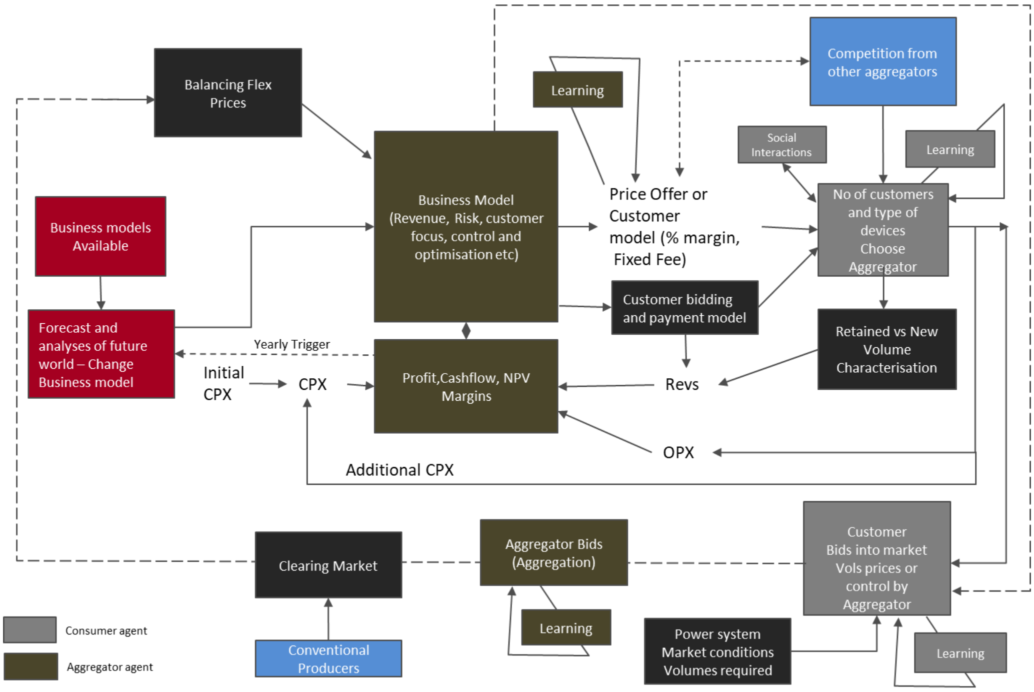

Figure 7-3: High-level block diagram of PyEMLab-Agg

Note the learning element in Figure 7-3 is based on a ZIP learning based element, but could be replaced by an alterantive RL algorithm. The ZIP learning algorithm uses its previous bids to update its new bid.

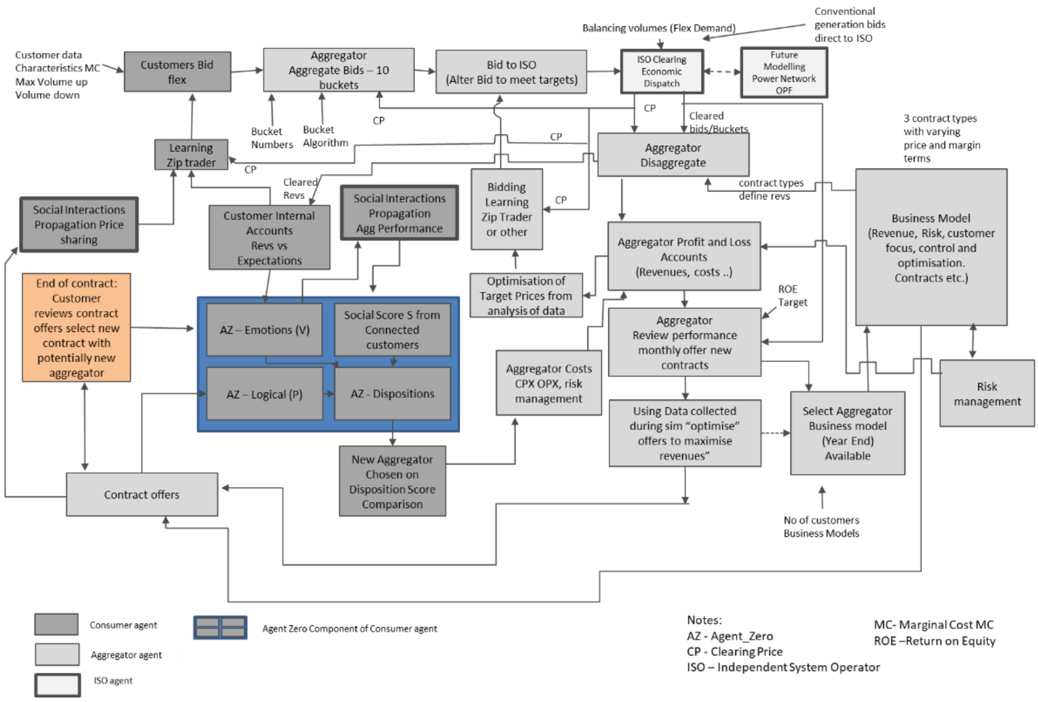

Figure 7-4: High-level interaction diagram of PyEMLab-Agg

The key novel elements of the model shown in Figure 7-4 are highlighted and discussed briefly below:

- It includes an Agent_Zero module that models emotions, social scores from interactions. The Agent_Zero module also reviews the performance of the contract from an economic point of view. It uses a multi accumulator approach to keep "scores" on all aggregators in the market and can "lock out" aggregators with really bad scores.
- Aggregators assess market conditions and use this data to perform an internal analysis so that they can optimize their Contract offers to customers looking for a renewal of their contract. This also includes changing the contract type offered.
- Customers review the aggregator and contract performance at the End of

Contract. Customers analyse their performance economically, but also use "scores" from their social and economic view of the aggregators.

- A Risk management module that uses a Monte-Carlo options approach to calculate risk for the bidding buckets. The risk for each individual bucket and contract type is calculated and is then rolled up into a portfolio view of the risk for the aggregator. This is used to determine the price of the hedge, as well as a decision on whether to take the hedge.
- A sparse matrix Social interactions model linked to each customer. A propagation module keeps track of messages passed to/from customers on the network.
- Aggregators can choose between multiple business models and have a module that is used to assess the future performance of those Business Models in the future. Historical performance data is used to forecast future values.
- Aggregator Bucketing – particularly in the context of using the Astropy algorithm, which appears to provide superior performance to more simplistic measures.

7.1.2 Model Simulation Speed

Many ABM frameworks make use of list processing techniques to update agent internal values. Code loops around agents; processes them and updates internal values.

For 50,000 plus agents this can be slow[191]. Array vectorization of calculations using matrices can significantly speed up these calculations and although more difficult to understand, results in significant speed improvements. The C based Numpy[192] or Xarray libraries in Python, provides an ideal framework for processing large numbers of agents in an array format and can be used to filter[193] those agents very quickly. The format also allows for the use of sparse matrix algebra. Use of a Cprofiler [531, 532] helped in reducing run times by an additional order of 50-80%. Run times for a 1-year simulation with 55,000 agents were initially of the order of 2 hours but this was reduced to 20 mins using vectorization.

7.1.3 Reporting; Using Hdf5

The original EMLab/PyEMLab used reporters to generate CSV files by "dumping" data at each time tick. The PyEMLab framework has been extended to store matrix or array output at the end of the run in the scalable and fast binary Hdf5 format [533, 534] using the Python based h5py [535] routines.

A list of tuples is used to define outputs, and the amount of data included can be altered. e.g.

[("name of output string", array_of_values_stored_in_array), ("clear prices", reps.clearpricematix), (("contract offers ", reps.aggcontractoffers) ….]

A hdfviewer such as HDF® VIEW [536] can be used to inspect, and or copy the

[191] Parallelisation would help in this regard.

[192] Numpy is used in this work.

[193] That is used to filter or select a set of agents on a particular node or select certain generating assets.

output, for use in other packages such as Excel, MATLAB or R and used for further analysis.

7.1.4 P&L Account and Balance Sheets

For further information on accounting and cashflows, the reader is directed to introductory accounting texts [537-540]. Separate Profit and Loss accounts, and cashflow statements for each of the aggregators is stored in memory during the simulation. Total sales revenues (volumes cleared multiplied by the clearing price), the cost of sales (in this instance the amount paid to the customers as part of the contract), the operating costs and the depreciation, corporate tax and so on are calculated as per standard accounting practice.

7.1.5 Herfindahl-Hirschman Index (HHI): Market Power

The Herfindahl - Hirschman Index (HHI) is a common measure of market concentration/power. It is calculated by squaring the market share of each firm competing in a market and then summing the resulting numbers. It can range from close to zero to 10,000.

$$HHI = S_1^2 + S_2^2 + S_3^2 + \ldots\ldots \qquad (7\text{-}1)$$

where S_1 is the market share (% expressed as a whole number) of company1 and so on.

The U.S. Department of Justice considers a market with an HHI of >2,500 to be a highly concentrated marketplace [541]. The Competition Markets Authority (CMA) in the UK typically regards markets with a "HHI below 1,000 as unconcentrated, markets with HHI between 1,000 and 2,000 as concentrated, and markets with HHI above 2,000 as highly concentrated". In 2017 the UK gas/electricity market had an HHI of 1599/1247 respectively [542](p20 and 87).

Six aggregators with equal shares would have an HHI of 1667. The simulation framework collects market shares and can easily calculate HHI using equation (7-1) through time as shown in the simulation output in Chapter 8.

7.1.6 Emergence

Emergence is an important concept in complex systems and at its simplest is the phenomenon where global behaviour arises from the interactions between lower level components. Wolf and Holveot [543] provide a working definition for emergence; "a system exhibits emergence when there are coherent emergents at the macro-level that dynamically arise from the interactions between the parts at the micro-level. Such emergents are novel w.r.t. the individual parts of the system."

Complex human/social based models are expected to have emergence, especially when agent learning is involved [544, 545] and detecting such emergence and understanding conditions under which it can occur is an important part of the motivation for building this ABM framework.

In general, automatic detection of emergence has proved to be difficult. However, a number of algorithms have been developed and some of these are available as open source libraries. EMBER [546] is one such library written in Java and has been used with a small ABM model written in Netlogo. Future work may incorporate these libraries.

Fractals Pink noise and Hurst Coefficient

Pink noise/Fractals are present everywhere in nature from earthquakes, the growth of trees, rainfall, and brain patterns [547, 548]. Fractals are seen to produce the same pattern at different scales, and they are, therefore, also known as scale free. Scale free signals exhibit a power law relationship where spectral power takes on the form:

$$P = cF^{-\alpha} \qquad (7\text{-}2)$$

where P is Spectral Power; c - a constant ; F - frequency and α is the scaling exponent.

In pink noise, the contribution of low frequencies is higher than white noise. Pink noise is scale free with a scaling exponent 0.5< α <1.5 (note that α=1 is a special case of pink noise).

The Hurst coefficient H (which will be discussed later) is related to the scaling exponent by the formula:

$$H = \frac{\alpha + 1}{2} \qquad (7\text{-}3)$$

Real world networks have a scaling exponent α which ranges from 0 - 2. A time series with an α =0 is random (H=0.5).

Bak [549] suggests that pink noise arises when a macro-level event is generated by a single micro-level event which, because of coupling, cascades its effect across many inter-related entities.

What is important here is the idea that fractal behaviour (pink noise) is a clear indicator of non-linearity and self-organization. However, it should be noted that although Pink noise can be a defining characteristic of emergence, it is a necessary and but not sufficient condition for proving emergence has occurred. Pink noise has a

Hurst coefficient ranging from [0.75,1.25] with a special case at $H= 1$ [550] and $\alpha=1$.

Thus the question is can we use this exponent, or other parameters like Lyapunov coefficients, in an ABM simulation to detect emergence? The answer of course is yes. In the context of this work, interactions at the micro level (customers, aggregators and market clearing) could result in emergent behaviour. Detection of such events could be made using Hurst coefficients.

Hurst Coefficient and its Meaning

The Hurst exponent (H) or coefficient is measure of long-term memory of a time series and was developed by Harold Edwin Hurst in his studies on hydrology in the 1950's [551, 552]. The Hurst coefficient can be calculated by following a number of steps as highlighted in [551], but the interest here is in the interpretation of its value through time.

"The *Hurst coefficient (H)*, is 0.5 for both white and Brown noise..... The Hurst coefficient of self-similar processes deviates from 0.5. For pink noise, $H = 1$"[194] [550].

$H = 0.5$	Brownian motion, (Random)
$0.5 < H < 1.0$	Persistent trending behaviour
$0 < H < 0.5$	Mean reverting or stable behaviour

Uses of Pink Noise in Simulations

Zhukov, Kanishchev and Lyamin [553] uses a methodology that detects changes in noise colour (pink, white and red) and shows that it can be used as an indicator of changes in historical processes. "In some cases, this indicator can enable one to

[194] Self-similar process -> Fractal.

establish the time, speed, and direction of state changes" and can be used to highlight or identify potential cases of emergence. Similarly, Dooley and Van de Ven [554] analyse complex organisational dynamics and categorise them by using different noise patterns. They use such noise patterns to help them hypothesize about a particular story, or causal process.

The Hurst component has also been used to predict turning points in financial markets or to identify market bubbles or financial crises [555, 556]. The maximal Lyapunov exponent has also been used to predict emergence in nonlinear systems in a variety of fields [557, 558], while [559] shows the correlation between Hurst indices and Lyapunov exponents.

Saxena and Saxena [560] propose the use of a Hurst exponent pattern approach with node connectivity to provide a better view of the "nodes influence potential" and claim that it provides a better algorithm for prediction of adoption rates in viral marketing. Although developed from a marketing perspective the concept of using a Hurst component to "quantify" and identify key influencer nodes might be useful in future analysis of the message propagation in the social networks modelled in this thesis.

As Python provides an open source library for calculating a Hurst index (hurst 0.0.5 [552]), a collection of Hurst exponents through time has been made during the simulations in Chapter 8, as a first step to help in detecting emergent phenomena and as a method to identify "turning" points in simulation dynamics. It may also be useful in providing a narrative like that discussed in [554], where the authors identify how noise pattern characteristics (pink, brown, white etc.) change through time, and propose to hypothesize about the underlying dynamic processes.

7.1.7 Temporal Interactions of Principal Actors

The interactions between aggregators, customers and the market clearing entity is represented through time in Figure 7-5. As discussed in section 2.7, customers and aggregators perform various actions at different times during the simulation, e.g. daily weekly monthly and yearly. The scheduler in the agent framework keeps an account of these times and sets and resets flags at the appropriate moments during the simulation. These flags are used by the agents to control specific actions at the appropriate times, e.g. domestic customers send out messages weekly to other domestic customers.

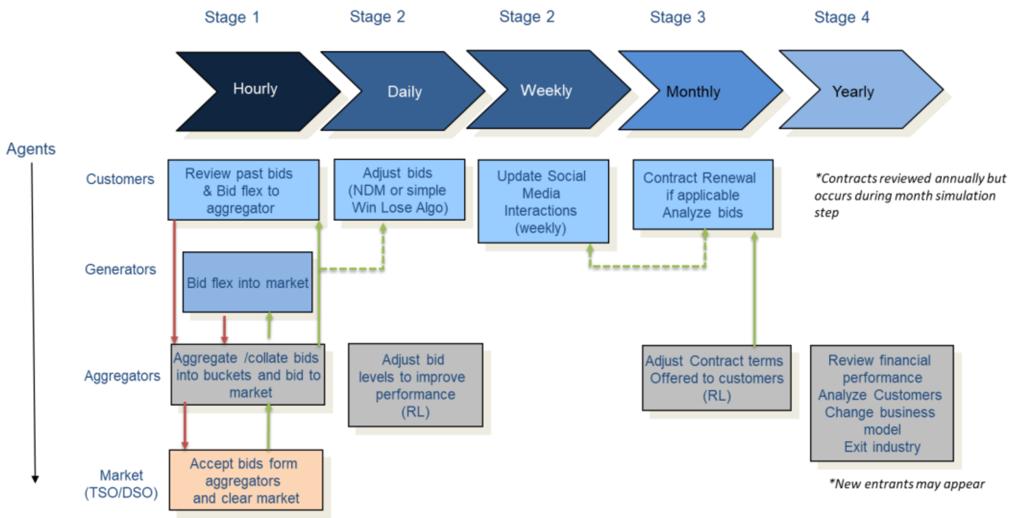

Figure 7-5: Overview of the actor interactions in ABM framework

In this simulation, customers bid upward and downward flexibility, hourly. Each customer sends out either an upward or downward flexibility bid. In addition, each customer provides one bid per hour.[195] Note in theory, Aggregators may allow customers to bid multiple segments, e.g. customer will supply downward flexibility of 3 kwh at £60/MWh and then a further 3kwh at £324/MWh and so on. The original SmartNet design also allowed customers to bid both upward and downward flexibility at different prices. Customer bid prices are based on customer's marginal costs, prior clearing prices and expectations about revenues for the year. Aggregators take these bids, and aggregate them as detailed in section 2.7. Aggregators adjust bids using a learning paradigm based on Cliff's ZIP Trader (Section 6.2.3), an analysis of prior simulation data and prior clearing prices. Generators bid at marginal costs but a sensitivity using a ZIP trading module is provided in Chapter 8. The ISO agent clears the market using economic dispatch and sends back cleared bids data to the aggregators and generators. Note that it is assumed here, that each aggregator sends out 10-bucket bids to the ISO every hour[196]. In future versions, where nodal pricing will be considered, aggregators would send out bids for each node. This would increase the number of bids that the ISO would need to clear. The current simulation considers only active power, whereas SmartNet considered both active and reactive power.

The following sections now detail the key mechanics associated with specific agents in this simulation framework.

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[195] This is probably a reasonable assumption. In a more sophisticated bidding structure both upward and downward bids might be made.

[196] This can be changed.

7.2 Aggregator Design

The aggregator design is based on the work set out in SmartNet for the Curtailed Generation Curtailed Load (CGCL) aggregator [8, 9, 82][197] and has been extended in this thesis to include an options based risk management module (Chapter 5), business models and accounting modules (Chapter 4), and includes a version of Dave Cliffs ZIP Trader (section 6.2.3) for aggregator price bidding. A block diagram of the main aggregator modules and functions is given in Figure 7-6.

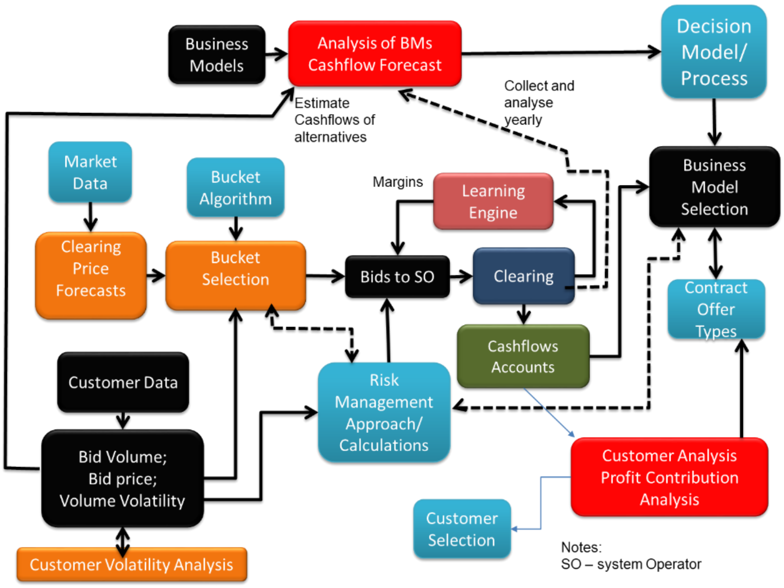

Figure 7-6: Aggregator functions; Overall approach

7.2.1 Agent Aggregation: Outline of an Agent Design and Bucketing

The aggregator/disaggregator agent simulates the aggregation/disaggregation of

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[197] Note the thesis author is the designer/researcher behind this agent.

bids from thousands of customers. For each hour, bids from customers (volume – kWh and bid price £/MWh) are combined into price "buckets"[198] to produce up to ten price volume bids per time step (either up or down). In effect, each aggregator is an agent (a software object), who stores the data from all the customers who have contracts with the aggregator.

In SmartNet, buckets are clustered by cost, but the concept can be extended to a more general clustering algorithm using multiple variables. In fact developing an appropriate clustering algorithm may give aggregators an edge in operating in this market. This thesis uses some simple algorithms discussed below and a more sophisticated algorithm based on Scargle's Bayesian Blocks [561]. However, these could be extended.

The aggregator sends out up and downward flexible bids e.g. for the next hour[199] to the ISO. In SmartNet, the aggregator sends out bids for the next 12 hours on a rolling basis, but in this simulation, only the next hour bids are provided. Note SmartNet looked at a number of bidding market designs including the use of a rolling horizon; bidding 12 hours ahead. The 12-hourly bids is useful for the DSO as it can plan further ahead. As the grid is not currently modelled in detail here in this work, there is no need to provide rolling look ahead forecasts. An hour was chosen as a reasonably small enough bid interval[200], although the various regulators are looking at

[198] See Appendix N for detail.

[199] In SmartNet, Aggregators can bid over multiple times frames – but this model assumes only hour ahead bids are provided.

[200] Smaller bid intervals would increase computational time proportionately. The model is able to easily switch from 1 hour bidding to 5 minute bidding.

5 minute bidding. Also, keep in mind that the aggregator might gain more experience if they bidding more frequently.

For each hour, the aggregator sends out bid buckets, which represents the aggregation of all of its customers bids. Each bucket represents a price range, e.g. 10-30, 30-70 £/MWh and an associated volume (see Figure 7-7). These price buckets will vary in range each hour and by aggregator, dependent upon customer bids.

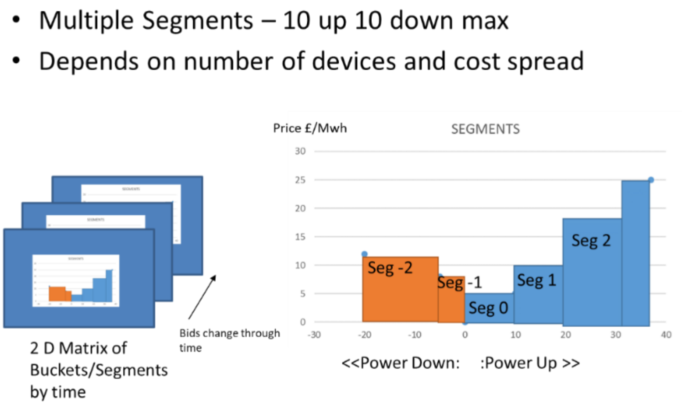

Figure 7-7: Aggregator bid structure overview; Hypothetical example

Each aggregator agent performs its own calculations and updates databases as necessary. Segment or buckets are identified using an index of [0,(N-1)] for upward flexibility and [-N,-1] for downward flexibility.

The key for the aggregator is to apportion thousands of bids to a set of limited buckets, e.g. 10, so that it maximizes its profits in the face of uncertain volumes and uncertain prices. Aggregators would, therefore, set the price ranges on these buckets to maximize their expected profit. Figure 7-8 shows a hypothetical example of the process with five buckets, represented as two arrays. Note in the representation shown below p refers to price not power.

Assuming continuous buckets, the bucket range of the i^{th} bucket could be represented as $p_i - p_{i+1,}$ where p denotes price. p_0 would be equal to the minimum bid accepted by the aggregator and p_6 would be set to the maximum bid. As p_i is adjusted, customer volumes are assigned to these buckets based on their bids.

	p1	p2	p3	p4	p5
Lower Level	**10**	**23**	**28**	**32**	**64**
Upper Level	23	25	32	64	102

pUpperj = pLowerj+1

Vol Assigned Mwh	**100**	**26**	**5**	**123**	**21**
Price Bid	23	25	32	64	102

- Bucket Size Variable – to maximise profit
- Price Bid – currently max of bucket but could be weighted Average
- Bucket p1 = Has all bids with 23 >Prices >=10
- Optimise choice of p1 – p5 to maximise profit, knowing a probability of cleared prices and with a limited amount of buckets

Figure 7-8: Bid buckets example; Adapting price ranges

The optimization problem is somewhat similar to a knapsack formulation [562] – but one in which the knapsack sizes can change – they are being optimized. This, when coupled with risk valuation, makes it a complex problem to solve. Genetic algorithms/evolutionary solvers could be used to solve this problem but this will be time consuming. In practice, the aggregator has to keep accounts of the types of contracts in the buckets so that it can calculate risk associated with each bucket, so the matrix structure inside the aggregator agent is more complex.

In reality, the aggregator will need to understand the power flow and voltage constraints on the system if it is to successfully optimize its portfolio of assets into buckets. This would mean that it will need access to a physical model and constraints of the network. Note that one possibility is that the DSO may provide this information in future years, in real time. Note because this work does not model the network in detail, there is currently no need for a “physical network model, but will be the subject of future work.

7.2.2 Bayesian Blocks Buckets: AstroPy Heuristic

In the hypothetical example shown below, the aggregator wants to select four bid buckets so that it maximizes its profits or revenues by doing so. The expected revenues in this case would be given by equation (7-4).

$$Expected\ Revenue = \sum_{i=0}^{n-1} VolumeMwh_i * Price_i * CDF_i \qquad (7\text{-}4)$$

Where:

- n : Number of bid buckets
- $Price_i$: Bid price of the i^{th} bucket. In the algorithm used in the simulation $Price_i$ is the weighted average price of all bids in the bucket.
- $VolumeMwh_i$: Volume in i^{th} bucket
- CDF_i : Cumulative distribution function of the clearing price and represents the probability that the bid price will clear. Data collected by simulation would be used to create a CDF function like that shown in Figure 7-9(c).

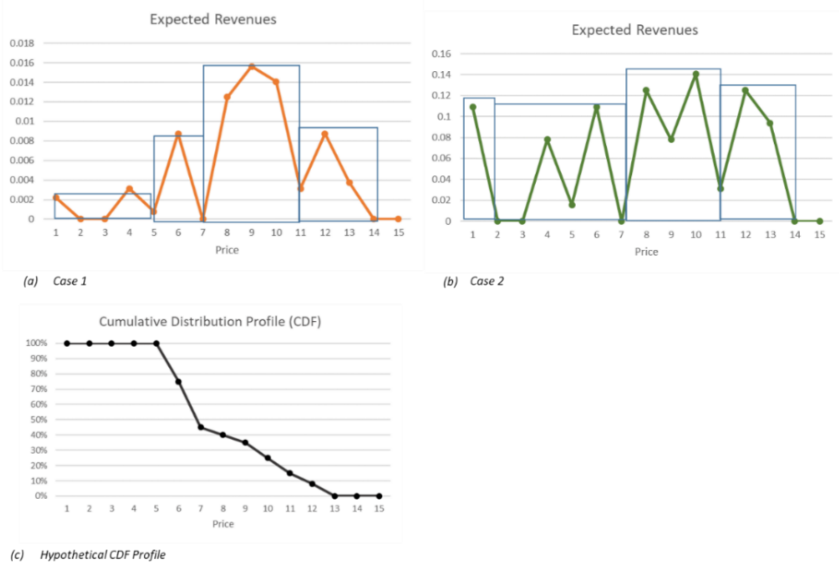

Figure 7-9: Bayesian block methodology

The Bayesian Block algorithm, tries to fit the resulting expected revenue profiles into a set of histograms like that shown in Figure 7-9(a) - (b). The number of blocks is dependent upon a factor set in the algorithm i.e. the gamma factor. This may produce many more, or less, buckets than required. Reference [561] does provide a relationship between expected number of blocks and gamma factors but it is found that this is not accurate for this simulation. It does provide a useful first guess and, with some trial and error, the expected revenue profile can be fitted to the appropriate number of buckets.[201] As will be shown in section 8.5.2 this AstroPy heuristic, as it will be called[202], provides the aggregator with superior results over simpler representations. Of course, a genetic algorithm or a bi-level optimization formulation might provide a more accurate algorithm, but the actual formulation of the

[201] The simulation estimates the number of buckets using the gamma factor initially and interpolates over a set of 10 points to determine the number of and best bucket sizes.

[202] The open source library AstroPy has Scargle's Bayesian Block algorithm embodied within it.

optimization problem is actually somewhat more complicated than that shown above, e.g. each bid would potentially be associated with different contract terms and risks. Computationally, this would increase run times significantly. For now, this optimization/portfolio problem is left for future work. This enables a faster simulation than trying to optimize the solution, which is non-linear in nature.

7.2.3 Aggregator Bucket Risk

Chapter 5 presented the calculation required to calculate risk for one bucket inside of the aggregator agent, but aggregator agents have in this instance have 10 buckets[203], so risk/option value is calculated separately for each bucket. The sum of each option value, associated with each bucket provides an overall risk value.

In addition, each bucket would have a different mix of contract types and parameter values. The algorithm for calculating the options for each bucket, therefore, has to account for this portfolio mix and is shown schematically in Figure 7-10.

[203] Note this is an input parameter.

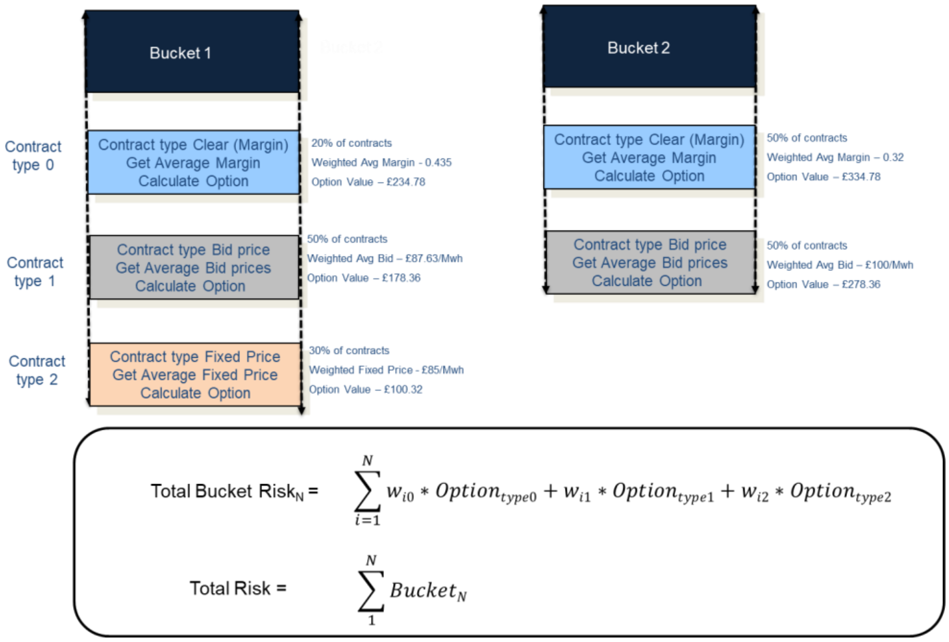

Figure 7-10: Aggregator risk calculation example

7.2.4 Aggregator Target prices: Adjusting bids to Account for Operating Costs

Aggregators need to provide bids that cover their operating costs and risks. In this framework, Aggregators currently use the ZIP trader algorithm (section 6.2.3) to adjust their bids. The original ZIP trader model used stock prices as the adjustment target or setpoint. In this model, target price can either be the greater of the last clearing price or a target price that looks to cover the remaining operating costs left in the year. Target prices can be set hourly, daily, weekly, monthly, quarterly or yearly, although the simulation results shown later in Chapter 8, use daily updates.

For example, at time zero, aggregator 2 estimates that it needs an average clearing price of £75.34 to reach its targets. After a review of its performance at the end of month 4, it estimates that it would require a target price of £261.76 for the rest of the year to meet target. The price is higher in this hypothetical example as the performance of the aggregator in months 1-4 has been poor. This would be the target price used in the ZIP trader algorithm assuming it was higher than the average of the previous clearing prices. Although this was used as the initial design for the aggregator price setting mechanism, it was found that as the prices were increased to meet targets, profits did not increase commensurately and profits over the year fell well short of aggregator requirements. Further analysis of the aggregator actions found that at the current costs, aggregators need around 6,000 + customers to break even. The average clearing price (CP) needs to be in excess of 100-120£/MWh (section 4.3.1) to cover expected profits. Simulation results in Chapter 8 with base case numbers indicate that aggregators cannot make profits, as they cannot bid low enough to displace bids made by conventional generation (for most of the time). Increasing aggregator-biding prices does not help in this regard, as it results in less aggregator flexibility volumes being accepted and lower profits.

If imbalance volumes increase through time and conventional generation is not increased, aggregators are seen to make acceptable profits. To alleviate the issues seen in the profitability of the aggregators, a slightly different bidding algorithm was incorporated that looked to maximise profits and was found to improve aggregator performance.

7.2.5 Agent Disaggregation: After Market Clearing

After clearing, aggregators would inform customers of the acceptance of their bid and provide payment as defined by the contract terms agreed with the aggregator. The aggregator would keep some portion of the revenues provided to them by the clearing operator (ISO), according to the terms of the customer contract. This means that the aggregator has to keep account of every customer in arrays.

7.2.6 Aggregator Offers to Customers

Offers are submitted to the market by each aggregator at the end of the month. Aggregators use simulation data to estimate the optimal choice of contract terms that they believe will maximise their profits. Appendix M provides details of the algorithms used in calculating the optimal offer.

As the months progress, the aggregator will have many different types of contracts to deal with, each potentially with different pricing terms. It, therefore, needs to keep account of these so that the appropriate revenues can be collected and paid to its various customers. In some cases, the aggregator will need to risk manage its profit and its portfolio of contracts. In this case, an option-based calculation (as detailed in Chapter 5) is carried out, to determine the value of the risk taken and, therefore, the cost of a potential hedge[204]. If the hedge is exercised, revenues are adjusted accordingly to take account of said hedges, i.e. revenues would be boosted to meet the minimum profit levels. As each bucket has its own option in this model, account has to be taken of multiple option positions. Note this option value also varies by contract type and contract terms so the aggregator needs to keep account of this.

7.2.7 Aggregator Business Model Selection

Aggregators, at year end, will assess their performance using the current business model. A review of business models would normally be influenced by a number of

[204] Hedge cost is assumed equal to the theoretical value of the risk.

factors (see Figure 7-11) but in this simulation only the economics will be used to assess the relative performance of business models. It is assumed that adequate resources are available and that senior management support changes in business model.

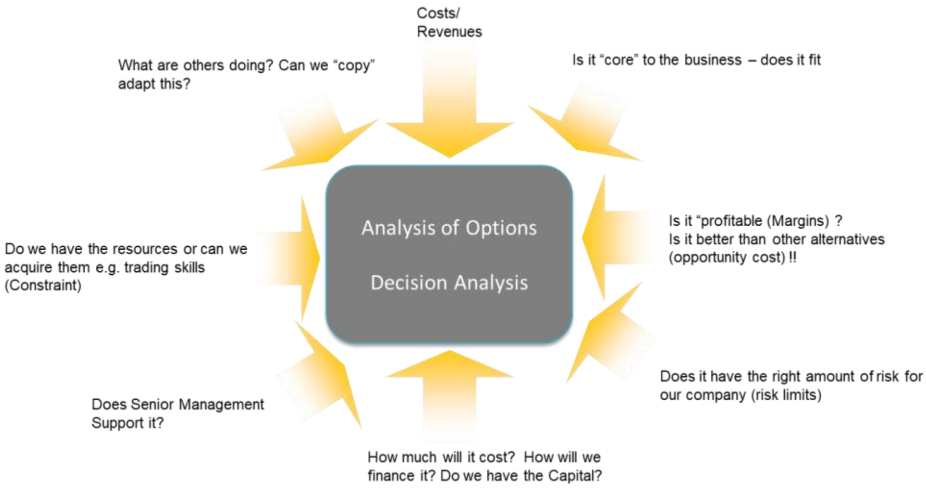

Figure 7-11: Business model selection

Historical data on clearing prices and the use of historical customer data (clearing prices, bids and volumes) are used to estimate the economic performance (NPV) of a new business model[205]. Competitive effects will be ignored, but assessment of competition could be included later. Additional descriptions for this process with equations is provided in Appendix I.

[205] Assumes same real revenue and cost base going forward for 20 years. NPV @ 10%.

7.2.8 Assumptions on Aggregator Costs in the Simulation

The models accounts for aggregator costs using the analysis presented in Chapter 4. A linear equation of costs with customer numbers is used to alter these costs throughout the simulation[206]. In practice, there would be additional staff/redundancy costs (unless the staff are on zero contracts) and additional monies may be available from the disposal of redundant equipment. These have not been accounted for in this simulation. There is not likely to be a great difference in costs in operating the different revenue models, so these are assumed to remain the same. There will be an additional cost if risk management is introduced both in terms of capital and operating costs. These are accounted for in the simulation if business models are switched.

7.3 ISO Agent: Economic Dispatch

The Independent system Operator (ISO) agent, which could represent a DSO/ TSO or some combination, uses a simple economic dispatch model. In future work a market clearing model based on OPF[207] will be used. In an economic dispatch (ED) model, prices in the balancing/flexibility market would be set by intersection of the marginal curves for upward and downward flexibility and balancing demand[208]. The approach is summarized in Figure 7-12, where a hypothetical supply curve for downward flexibility is shown on the top left (showing marginal prices vs negative

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[206] That is, it is dependent on the aggregator customer numbers, and will change throughout the simulation.

[207] See comments below for the potential impact on the results.

[208] Account is made for distribution and transmission losses using data from Ofgem.

balancing demand) and upward flexibility on the top right. These curves may have different shapes as well as different overall volumes. An example of a potential net imbalance volume path is shown in the bottom of Figure 7-12 through time.

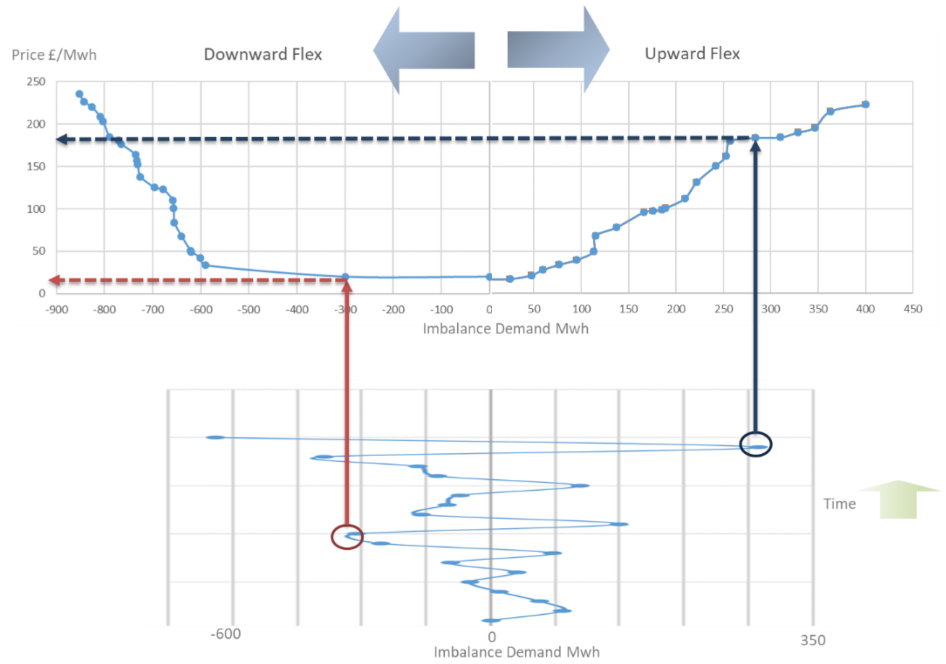

Figure 7-12:Upward downward flexibility and balancing demand: Price setting

Depending upon the sign of the net balancing demand, it will intersect either the downward or upward flexibility supply curve in the place shown by the vertical arrows. Prices associated with the supply curve at this point are shown with the dashed horizontal arrows.

7.3.1 OPF vs Economic Dispatch

The ED methodology was used to calculate one "zonal" price for the case study, but as stated previously it is the intention to extend this work to include a full OPF simulation. Ganga [563] provides an analysis of the Australian power market and shows that a nodal approach (OPF) would result in prices in the same areas that are some 25-100% higher than that calculated from a zonal approach (see table 5.1 and 5.2 in the reference). This will depend upon the network involved in the area (i.e. congestion in such areas) and the supply curve of the generation involved. Note some nodes will exhibit higher prices and some lower. Egerer, Weibezahn & Hermann [564] analyse the impact of a two price zonal market (2 Nodes) on the German power market over one and show that the price difference for two zones over one zone are 1.4- 10.2% higher (table 3 in reference). They also analyse power and monetary flows under one, two and four zones in the German market. Although the paper does not provide detailed numbers, it appears that, the 4 zone case results in price differences of 26-59% .

Choice of a market clearing mechanism and particularly the location of zones or the location of congestion will significantly affect power and monetary flows. Modelling of aggregators on multiple nodes will be required in this scenario and increases the complexity and run times of the model. The SmartNet implementation uses an OPF model of the network and provides a methodology for incorporating aggregators into a network formulation of a distribution grid. Aggregators in this model bid flexibility at different nodes. In a recent proposal National Grid ESO has suggested the use of a 800+ nodal model for the UK flexibility market [565].

7.4 Domestic Customer Agent Design

Data is provided to customer agents using an agent factory at the beginning of each simulation. Data is read from a CSV file defined by name in the scenario file and includes data on:

- Marginal bid costs for upward and downward flexibility. Note these are costed differently. Costs are based on work from references [566, 567].
- Upward and downward flexibility max volume values. Note flexibility availability is likely to follow a seasonal pattern (Fig 20 in [77]) so the simulation shapes, maximum flexibility availability vary throughout the year.
- Starting contract terms data; type and parameter settings e.g. fixed price, margin% is provided as an input.

Agents have been randomly assigned a starting contract value and randomly assigned to a 50,000 node social network[209]. The same social network assignment is used in all the case studies presented unless otherwise stated.

7.4.1 Domestic Customers Actions/Roles

In summary, customers perform the following various functions in this model represented in block form in Figure 7-13:

- Bid hourly flexibility volumes with a price (£/MWh).
- Adjust those bids every hour[210] using a learning algorithm (ZIP).
- Keeps accounts of its revenues and compares this to its expectations (a CSV input).

[209] One agent, one node.

[210] This can be changed to daily, weekly and so on.

- Updates its emotions based on aggregator performance in relation to expectations; potentially sends out a message weekly based on its emotions as discussed in section 6.4.
- Accepts messages from connected agents and further updates its emotions[211].
- Updates the Agent_Zero dispositional score every month and uses the average of dispositional scores from connected agents (Social Influence S Agent_Zero).
- Every year, at the end of a specific month defined by the input data, customers review their contracts. Customers review the various aggregator offers by comparing them on a social, economic and emotive basis (as per Agent_Zero section 6.4). A new aggregator (if applicable) is selected for the coming contract year; currently the simulation is fixed at 12 months but future work would allow variable contract lengths.

[211] Messages accepted with a probability of 0.3 (P_{rx}) in base case. This threshold can be changed.

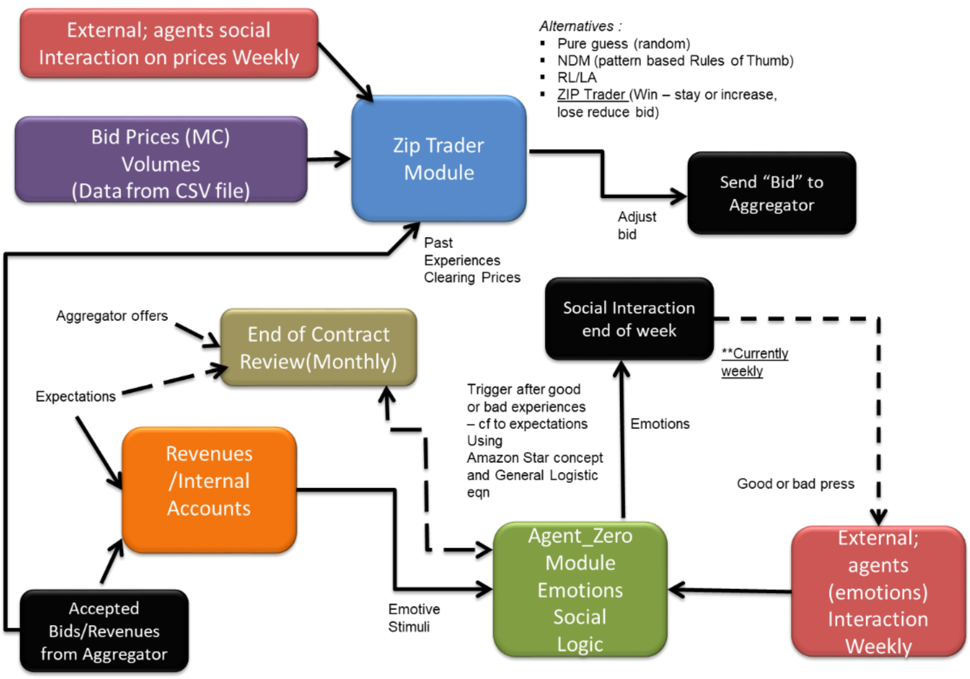

Figure 7-13: Customer functions: Overall approach

More detailed actions associated with domestic customer agents are shown in Figure 7-14 - Figure 7-16.

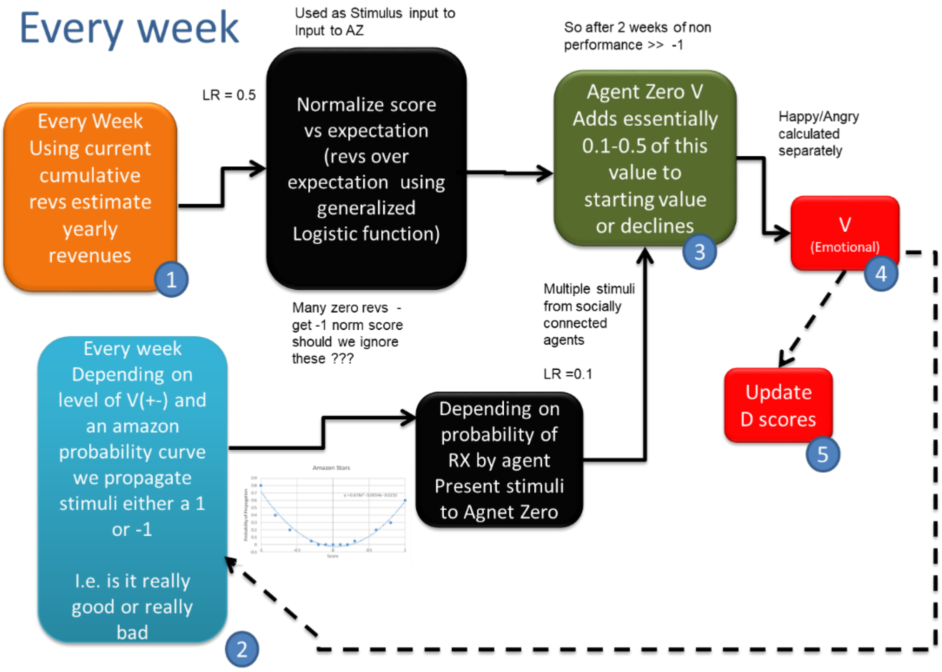

Figure 7-14: Customer functions – Weekly

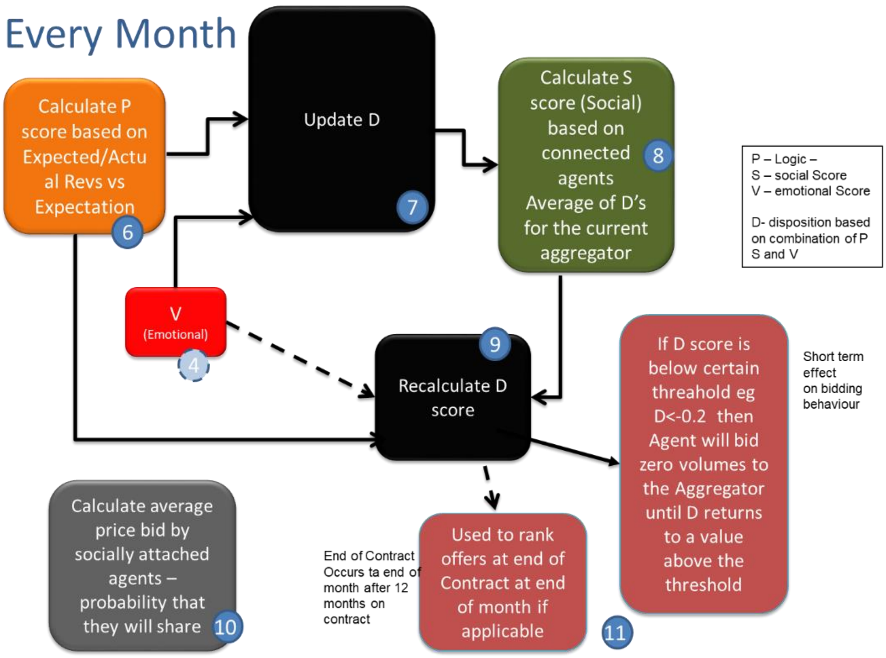

Figure 7-15: Customer functions – Monthly

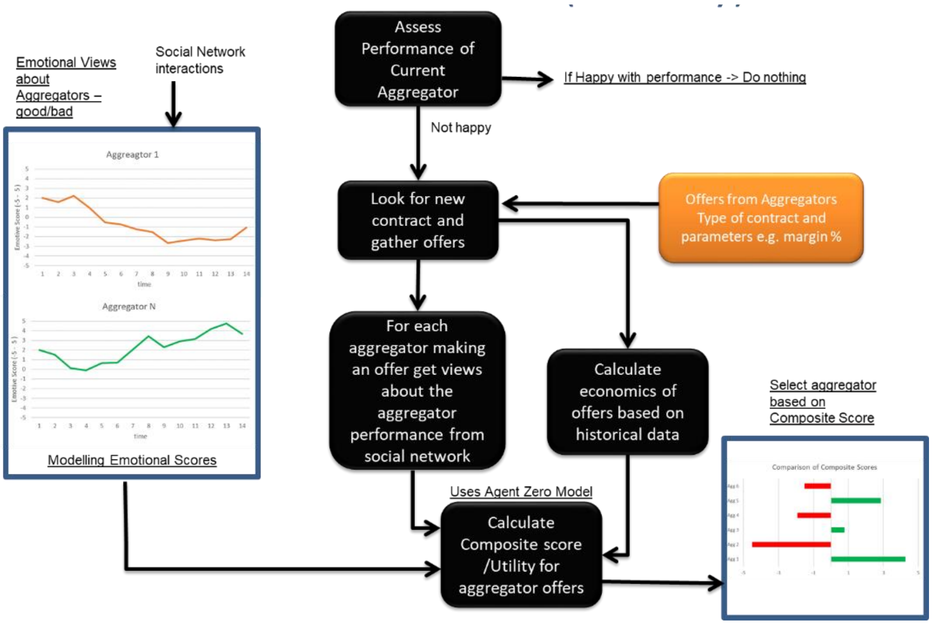

Figure 7-16: Customer functions – End of contract year/end of month; Selecting a new contract

7.4.2 Network Gossiping: Trust and Propagation

The premise of the modelling of customer interactions on social networks is that customers will "gossip" and swap views about the companies with which they are engaged. They may share price bids or contract information, or spread rumours or views/feelings about companies. The aggregator companies could also spread information but this will be ignored here for now. Such interactions can be represented as multi-layer social interaction networks, with different customers interacting on different issues with different customers (Figure 7-17).

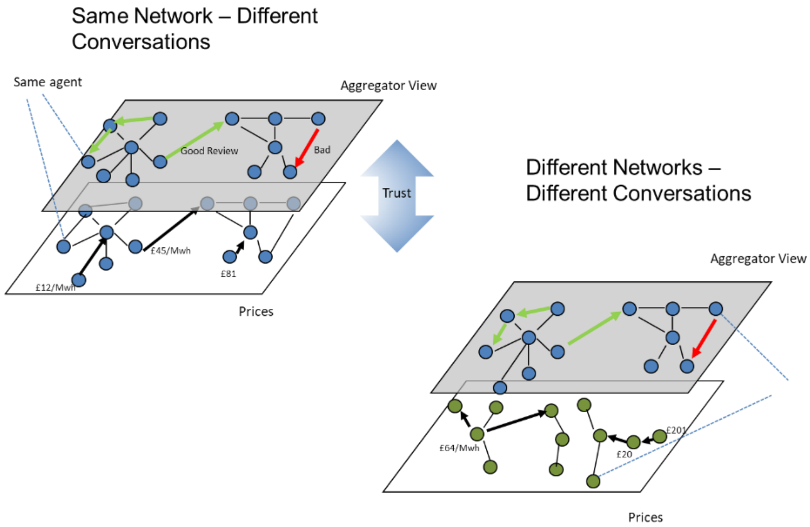

Figure 7-17: Gossiping in social networks; Multiple levels.

Although not shown, there is a third interaction layer that could be added to this set, namely, the power grid that each agent is attached to. Note the current model doesn't include a power grid layer. In effect, the model could have three interacting layers and potentially more[212]. Networks are stored as adjacency matrices in a sparse format so that matrix algebra can be used.

7.4.3 Message Propagation by Domestic customers

Propagation of messages by domestic customers is based on the combined score of emotions (angry and happy; $V = V_{happy} - V_{angry}$). The hypothesis is that the more angry or more happy that you are with a product, the more likely you will be to spread the word, either good or bad about that product on social media. Using an analysis based

[212] E.g. transportation layer for EV cars using off home charging. This would be linked to the power grid. Note only two interacting layers are included.

on the "Amazon stars system"[213] [568], for good and badly rated products, the probability of getting a good rating vs a bad rating has been calculated from statistics of reviewer numbers[214]. Note the probability of propagation of the message depends upon how bad or how good the aggregator is viewed[215]. The probabilities that have been used in this simulation are shown in Figure 7-18 below using a normalised score of [0,1] (happy) or [-1,0] (angry).

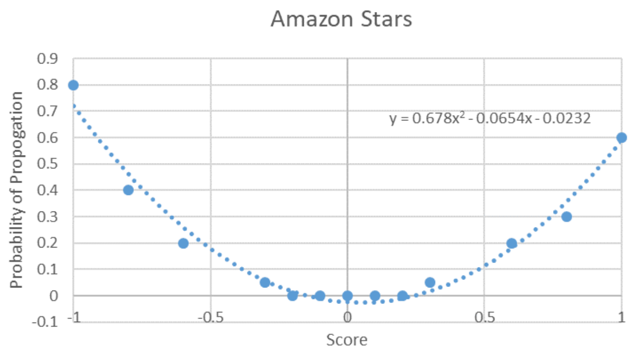

Figure 7-18: Probability of propagation based on Amazon stars

Normalised propagation scores are estimated from a general logistic equation[216] using the ratio of forecast yearly revenues over expected yearly revenues (equations (7-5) – (7-7)) adjusted for the weeks already elapsed, i.e. the value is scaled to

[213] Note EBay uses a similar system – with good and bad reviews adding to points that contribute to a score of [1,5]. Note that in this work we use a range of [-1,1]

[214] This makes the assumption the probability of passing on a "good" social media message is related to the proportion of 5 or 4 star reviews. Similarly for bad reviews with 1 or 2 stars.

[215] That is, does it have 1 or a 5 star rating.

[216] The concept here is that customers will be looking for an expected revenue. Amounts over this expected revenue will contribute to the normalised score. Based on internal discussion once the raw score is 1.5 times the expected revenue, the normalised score from the logistic equation would saturate at 1.

represent revenues over 1 year.

$$Forecast\,\mathrm{Re}venues = \frac{CurrentTotalofYearly\,\mathrm{Re}venues}{NumberofWeeksElapsed} * 52 \quad (7\text{-}5)$$

$$RawScore = \frac{Forecast\,\mathrm{Re}venues}{ExpectedYearly\,\mathrm{Re}vemue} \quad (7\text{-}6)$$

$$NormalisedScore = GenenarlLogistic(RawScore - 0.5) \quad (7\text{-}7)$$

These form the basis of a stimulus to the emotion agent zero accumulator discussed in section 6.4. See Appendix P for more details on the General Logistic equation and its use in the model. In addition, the latest prices are shared over a social network and is used as an input to the ZIP trader algorithm. Future work could calibrate these curves using customer survey data.

7.5 Industrial Customers

Industrial customers have been designed on the same framework as the domestic customers except that they do not message, propagate or interact on a social network. Industrial customers are assumed to bid marginal costs without adjustment. Marginal costs are based on work presented in [567]. However, code infrastructure exists to allow the easy addition of ZIP trader logic. As with domestic customers, industrial customers may bid to aggregators in the same manner. Bids from both domestic and industrial customers are processed as “one type” in the aggregator.

Industrial customers are assumed to use one contract type (pay a percentage of the cleared price to the customer) over the duration of the simulation and do not change contracts, although this assumption can be relaxed.

7.6 Generators

Large conventional generators bid directly to the ISO and do so by bidding marginal costs provided in the input data. Note distributed generation or more generally, DER's, are represented in some of the domestic customers. The input data contains a variety of different types of generation and associated marginal costs. A ZIP Trader module is temporarily added to one case to explore the effects of generators bidding on clearing price output (Case 12 in 5-year simulation).

7.7 Validation and Verification

Sargent defines verification as ""ensuring that the computer program of the computerized model and its implementation are correct [569]. That is, does the computer code work right. Model validation is defined by Schlesinger as the "substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model" [570]. That is, does it do what it was designed to do and represents a realistic future low carbon distribution network flexibility market.

In terms of verification, unit testing of individual models has been carried out in accordance with standard software principles. Code was tested, as it was coded. For example the output of an excel test model of risk management options (described in Chapter 5) was used to test the output of the equivalent Python code. The base structure is based on a model that has also been heavily verified.

7.7.1 Validation of Socio-behavioural Models

Validation of socio-behavioural models is known to be difficult [571-573]. This is especially so, as this is a simulation of a future market that does not currently exist.[217] This makes it difficult to statistically test the output using hypothesis testing or distribution analysis, as is typically the case in engineering or science simulations. Human behaviour further complicates the matter as humans adapt, causing non-linearity and non-stationary output. Emergent behaviour is also likely to be seen in these types of simulation.

Carey et al., have proposed the use of validation in parts and incremental validation[218] for social-behavioural models in [572]. That is, to validate inputs processes, and input to output separately, but without data this is difficult to perform.

Therefore no silver validation bullet exists for the ABM domain, but Nikolic, van Dam, and Kasmire [574] provides useful advice on developing and validating ABM models for use in a socio-techno setting. Section 3.10 of this reference highlights and provides examples of the uses of the various methods (See below). Note that the approaches underlined are those that are thought to be applicable for this task in this thesis:

- Historic replay;
- <u>Face validation through expert consultation</u>;
- <u>Literature validation</u> and

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[217] Which results in a lack of real data on which to validate.

[218] Model validated in steps with each step adding more complexity.

- Model replication (also known as triangulation)

Sargent [569] provides a list of similar methods but provides additional approaches that are summarised below:

- *Animation*: The model's operational behaviour is displayed graphically as the model moves through time.
- *Comparison to other models*: Simulation model outputs are compared to known results of analytic models.
- *Degenerate tests*: The degeneracy of the model's behaviour is tested by appropriate selection of values of the input and internal parameters.
- Event validity: The 'events' or occurrences of the simulation model are compared to those of the real system to determine whether they are similar.
- *Extreme condition test*: The model structure and outputs should be plausible for any extreme and unlikely combination of levels of factors in the system.
- *Parameter variability–sensitivity analysis*: consists of changing the values of the input and internal parameters of a model to determine the effect upon simulation output.
- *Predictive validation*: The model is used to predict (forecast) the system's behaviour, and then comparisons are made between the system's behaviour and the model's forecast to determine whether they are the same.
- *Structured walkthrough*: The entity under review is formally presented usually by the developer to a peer group to determine the entity's correctness.
- *Trace*: "The behaviour of a specific type of entity is traced (followed) through the model to determine whether the model's logic is correct"

Those that are underlined are considered applicable methods for this work.

7.7.2 Additional Validation Methods and Comments

Causal Mapping

Validation can be achieved in part through causal mapping (p 29 in [575]). Causal mapping can be achieved by using Fuzzy cognitive Networks (FCM), System Dynamics (SD) and Bayesian Belief Networks (BBN), although FCM is considered a good method in the light of its ability to deal with uncertainty in a computationally efficient manner (p589-589 in [576]). It is also considered an applicable method of validation for this work.

Parameter Sweeps/Sensitivity Analysis/Exploratory Model Analysis

Broeke, van Voorn and Ligtenberg [577] consider a number of sensitivity methodologies for ABM analysis as the sensitivity analysis helps analysts to understand ABM dynamics, and provides a platform on which the researcher/analyst can debate the validity of the output. Exploratory Model Analysis (EMA) is a systematic method aimed at exploring deep uncertainty in models so allows exploration of the parameter space. It has been used with system dynamics models, and in a few instances with ABM models [426, 578-580]. Although this work did not use a full blown EMA methodology, parameter values were varied together over what was considered realistic assumptions. Hundreds of simulations were used to explore the parameter space and were used in later analysis to help understand key drivers and the extent of model output (see Chapter 8).

7.7.3 Validation Approaches used in this Work

First, the validity of the individual agent's behaviours has been validated separately using subject experts[219] and triangulation with other models. Second, work from SmartNet (literature validation and triangulation) provided some clues as to how the model might operate, although the current model has extended the SmartNet model somewhat. Third, "toy models were constructed in Excel, providing an aid to help in understanding of the ABM system dynamics. Fourth, a linearized model and its associated visualisation constructed from a parameter sweep (analysed with SPSS (see section 8.2) provided a useful tool to help in understanding and validating the output of such a model.

Finally, a simple FCM model of the simulation of the model was constructed to help in understanding some of the more unusual results e.g. risk effects at odds with the model developed in Chapter 5 or target price interactions on bidding (see section 8.8). In some instances, this resulted in a re-specification/coding of the model.

Together, these various validation methods provide a degree of comfort that the model is both sufficiently robust in its representation of a future low carbon network with flexibility, and allows us to extend the methodology with a degree of confidence. Albeit, it is recognized that further work on validation will be required once markets are established and data is made available.[220] Finally, it is important to recognize that "the value of multi-agent models lie in their ability to explore and inform us about how a system might operate under different conditions"[573], to present plausible future paths and not necessarily to provide accurate predictions or single answers.

[219] Discussions with colleagues and Industry and energy association contacts.

[220] Note this may be some years away.

7.8 Discussion: Further Improvements of the Model

Electric Vehicle (EV) flexibility is not adequately represented in the approach discussed above. There are currently no EV ABM models based in Python that currently take account of pricing. A Python prototype that simulates EV drivers in the Netherlands using data and modelling methodology from work outlined in [581] has been constructed[221]. Although we have not yet linked that model to PyEMLab or to the aggregator simulations, it would be a relatively simple task to do so. Daina et al [582] have developed a methodology that incorporates charging price as one of its variables and uses stated response surveys to create a linear based algorithm/heuristic that is used to choose from a variety of discrete options e.g. charge, no charge or stay at home. In the longer run it is intend to incorporate Daina et al's, methodology and the model in [581] into PyEMLab/PyEMLAb-Agg.

Note that none of the ABM EV models that have been investigated incorporates Vehicle to Grid (V2G) interactions i.e. selling battery storage back to the grid. Storage decisions via a storage aggregator has been modelled in the SmartNet project [6] and could also be incorporated later.

7.9 Chapter Summary

A Python based object-orientated ABM simulator has been built based on the Java EMLab model. This framework has been extended to model adaptive customer and aggregator agents providing flexibility bids in a future low carbon distribution

[221] Drivers do not account for pricing signals in this model.

network. Customers have been provided with human like behaviour using the Agent_Zero framework. Aggregators have been modelled as corporate entities and include the risk management valuation methodology discussed in Chapter 5.

The PyEMLab framework has been further adapted to provide a vectorised agent model that runs 10-20 times faster than the original list processing/streams based model. It also believed that this is the first use of Dave Cliffs ZIP Trader and the Agent_Zero framework in an aggregator power domain setting. The framework provides an original contribution to the art as it is:

1. The first application of an extensible Python based ABM framework that includes the interactions between emotive domestic customers, competing aggregators and independent system operators in a power domain setting.
2. Includes corporate aggregator's business models.
3. Introduces corporate risk management techniques.
4. Incorporates contract adjustments for customers.
5. Uses a large social gossiping network that is used to affect emotions.
6. A tool that uses a novel extension of the Agent_Zero framework to model emotions, economics and social impacts.

The next Chapter uses the PyEMLab-Agg framework and the agents discussed above to simulate customer and aggregator interactions in a more realistic setting. Simulation results for many different assumptions are provided.

Chapter 8

The Effect of Aggregation on Market Evolution: ABM Simulation Case Study Results

Aggregation and aggregators will form an important element of a future low carbon network, as they will be crucial for the proper functioning and future development of such networks in many countries. Aggregators as corporate entities will be required to turn a profit, provide a high quality service to their customers while competing with other aggregators and other flexibility suppliers. The interplay between customers, aggregators and other market participants would determine whether aggregators and customers are sufficiently compensated. Aggregators that lack sufficient revenues will go out of business whilst aggregators that fail to secure enough competitive bids will fail to meet customers' expectations, potentially resulting in the withdrawal of flexibility from the market. Unprofitability or the withdrawal of such flexibility will affect the ability of the market to provide future savings and the investment required in infrastructure [10-13].[222]

To understand these interactions an illustrative case study consisting of 50,000 domestic customers, 4,500 SME'S (industrial customers), and six aggregators are modelled. Initially each aggregator has around 8,000 domestic customers, and 750 industrial customers, a customer mix that should initially provide a reasonable profit

[222] Flexibility services will reduce the need for infrastructure reinforcement.

to each aggregator (analysis in section 4.3)[223].

Key Questions

In the context of aggregator competition and evolution, clearing prices, customer revenues and aggregator profitability, there are number of key questions that this framework can answer (see Table 8-1 column 1). Note this is not an exhaustive list.

Question	**Type of Question**	**Results Section**	**Overview/Comment**
1. What are the key drivers in this simulation?	G	8.2.2	Multiple runs have been used to analyse key drivers in the simulation and have been used to build a "simplified" linear model of various outputs.
2. What is the effect of imbalance volumes and flexibility on clearing prices and customer and aggregator revenues?	G	8.2.2	Imbalance volumes and the amount of flexibility services available, are obviously a key driver of the simulation and prices in particular.

[223] Six aggregators were chosen as this is considered an appropriate number for a well-functioning competitive market (see Appendix A.1). As shown in section 4.3, 6,000 to 10,000 customers would be required for an aggregator to break-even. So with six aggregators, around 36,000 - 60,000 customers would be required to simulate a well-functioning market focused on flexibility provision. Note that imbalance volumes are used as a surrogate for future flexibility volumes.

Question	Type of Question	Results Section	Overview/Comment
3. How does elasticity of demand affect the simulation	G	8.3.1	Demand for flexibility services is fixed in the majority of the simulations. This set of simulations looks at the effect of incorporating a flexibility price element (price changes flexibility requirements) into the simulation. Overall, it looks to have a small impact of the simulations, but is seen to be greater at higher prices as would be expected.
4. What is the impact of bidding behaviours and contract types on price evolution?	G	8.3.2	Shows short-term price evolution for simulations using different starting contract conditions. A case using marginal price bidding is shown against customers and aggregators using the ZIP trading bidding module. Significant price differences can be seen between having a diverse set of contracts at the start of the simulation and having just one type. Bidding behaviour raises clearing prices.
5. What is the effect on the long terms dynamics of the market under different scenarios?	G	8.3.3	Uses Hurst Exponent to show how different scenarios changes the simulation dynamics. Uses many cases.
6. How does the type of social network affect price evolution?	S	8.4.1	Simulation results shown using a variety of social network structures (Section 6.3)
7. How does propagation in social networks affect the simulation?	S	8.4.2	Simulations with and without different types of social networks attached.

Question	Type of Question	Results Section	Overview/Comment
8. What is the effect of aggregator numbers on price evolution?	A	8.5.1	Simulations using 1 -6 aggregators to show the effect on the simulations. Fewer aggregators results in higher average clearing prices.
9. How does the bucket approach affect aggregator profits?	A	8.5.2	Various bucketing approaches for Customer bids are used to estimate aggregator daily profits. Significant differences occur.
10. What are the effects of the underlying aggregator costs on price evolution?	A	8.5.3	The base case simulation uses Aggregator capital and operating costs as derived in section 4.3. Sensitivities are shown for different operating costs.
11. What effect does aggregator risk management have on price and customer evolutions?	A	8.5.4 (Figure 8-17)	Figure 8-17 shows a simulation with all aggregators with risk management and without it. For most of the time, there are small differences but risk management can at times reduce clearing prices by over £300/MWh (for ~100 hours per year).
12. Aggregator Preference: Do customer agents change aggregators often?	A	8.5.5	Uses a selection of Key Agents to monitor the selection of aggregators by them over a 5 year timeframe
13. What does aggregator market share look like (Customer Numbers)? How does this impact on HHI under different scenarios?	A	8.5.6 & 8.5.7	Simulation of aggregator shares using different scenarios. In certain cases some aggregators reach near zero market shares and others become dominant in the market. This would not be a good market outcome. Section 8.4.5 extends the analysis on market share but focusses on contract type and includes a no propagation case

Question	Type of Question	Results Section	Overview/Comment
14. How often do Aggregators change Business Models?	A	8.5.8	Five-year simulation of six aggregators, showing how business models change each year under different scenarios. One aggregator never changes its business model and others change 3-4 times over the five-year period.
15. How do Aggregators view risk over time?	A	8.5.9	Calculates min max and average aggregator risk premiums over time under different scenarios. The "No Propagation" case increases risk substantially.
16. How does the Agent_Zero framework (AZ section 6.4) perform in the simulation? How does the selection of weights in the AZ modules (emotion, logic and social influence) affect the output?	AZ	8.6.1	Simulation using different weights in the AZ model. Difference in clearing price can occur using different weight assumptions.
17. Longer Term Impact on the evolution of Agent Zero Values e.g. emotions, social network scores etc?	AZ	8.6.2	Uses a selection of Key agents to monitor Agent Zero values using a variety of scenarios.

Note: Question Type G-General, S–Social Network, A-Aggregator, & AZ-Agent_Zero

Table 8-1: Key Questions answered in the Chapter 8 Simulations

By combining the various elements of the previous chapters, many simulations of the PyEMLab-Agg framework have been performed, with the aim of answering these various questions. The results associated with the questions are presented in the various sections as highlighted in the third column of Table 8-1. Questions have been grouped by question type (Column 2: G-General, S–Social Network, A-Aggregator, & AZ-Agent_Zero)

Initially, section 8.1 provides an overview on the simulation by presenting a business as usual case, discussing the stochastic nature of the simulation and introduces the idea of key agent tracing. Secondly, an analysis of the significance of the parameters used in the simulation is given using output from a statistical analysis package (section 8.2) and is used to answer the first two questions. Next, results are presented for the questions in Table 8-1 (section 8.3- 8.6). Section 8.7 presents the benefits of aggregation to the various stakeholders and considers the impact of aggregator competition on the market. Section 8.8 provides an example of where fuzzy cognitive mapping has been useful in understanding some of the simulation output and finally results are briefly summarized and discussed in section 8.9. Examples of data input used in the simulation are provided in Appendix F. The Chapter structure is summarized in Figure 8-1.

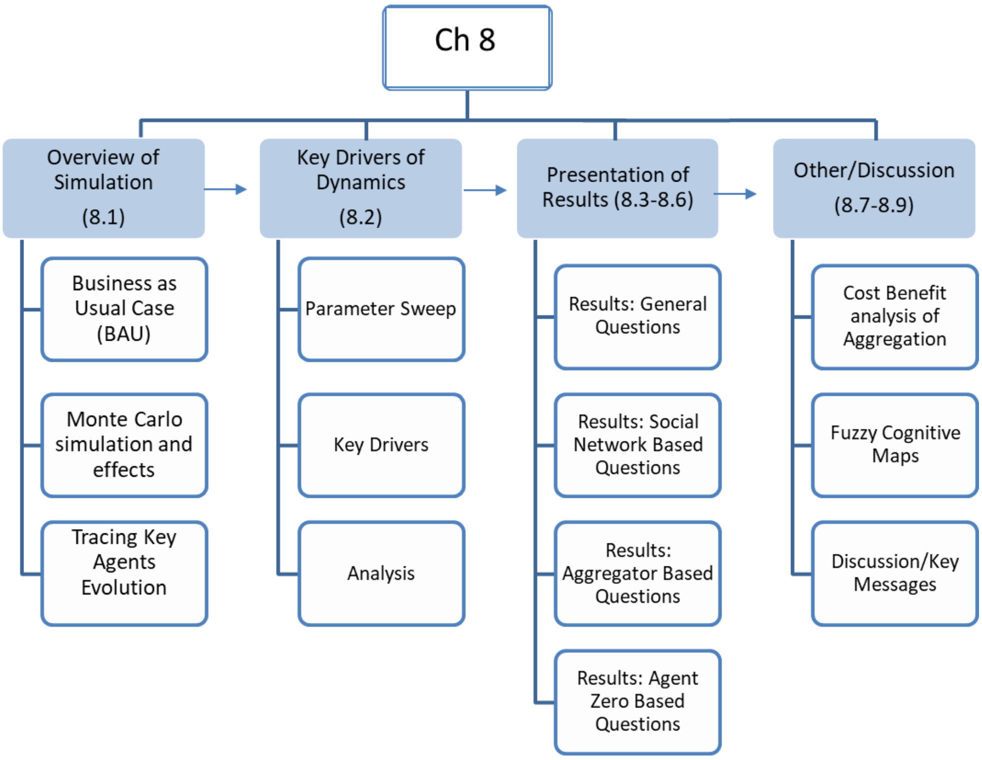


Figure 8-1: Overview of Chapter 8

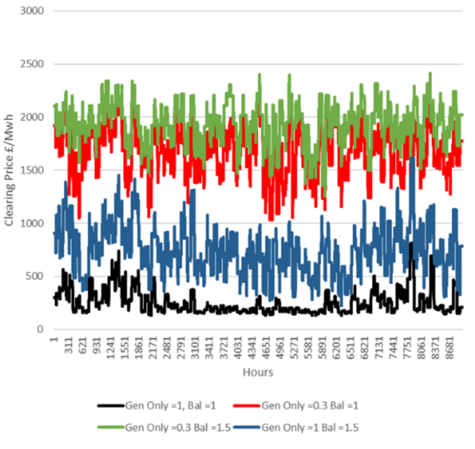
8.1 Overview of Simulation

8.1.1 Business as Usual (BAU): Conventional Generation Providing Flexibility

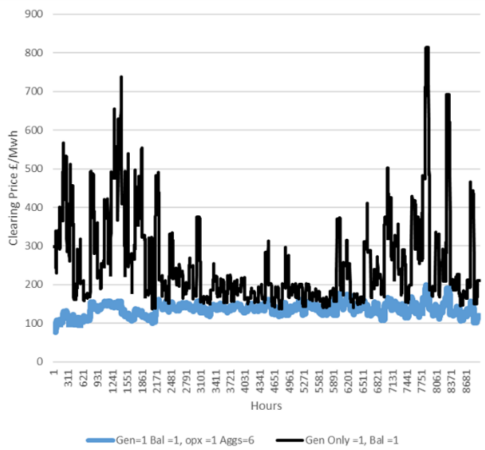
To assess the impact of aggregation in this work, simulation runs are compared to a base case that reflects the market without aggregation, referred to as the business as usual case (BAU). Figure 8-2 shows the balancing clearing price (CP) evolution over one year for a generation only and the equivalent six-aggregator case providing flexibility in competition with said generation flexibility[224]. Note paths are dependent

[224] Generators are assumed to provide 5% of their maximum capacity as flexibility. In addition the case study profiles have been sized to meet total demand.

upon assumptions associated with imbalance volumes and generation flexibility levels. Sensitivity factors for example Gen flexibility factor (e.g. Gen=1) and an imbalance volume factor (e.g. Bal =1) are used to multiply the data provided in the base case[225].

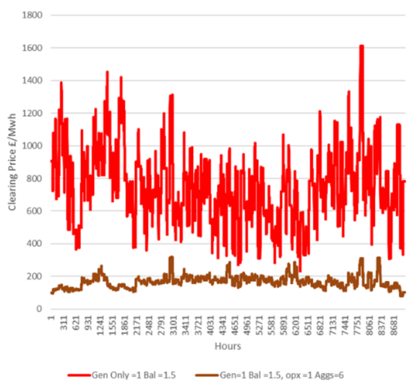


(a) *Clearing Prices for Generation Only for varying assumptions*

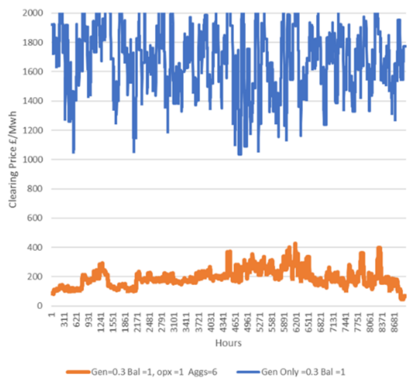


(b) *Clearing price Comparison between Gen Only and 6 Aggregator case; Gen Factor =1;OPXCPXfactor=1; Bal demand Factor =1*

Figure 8-2: Business as Usual Case: Only generation provides flexibility



(a) *Clearing price Comparison between Gen Only and 6 Aggregator case; Gen Factor =1;OPXCPXfactor=1; Bal demand Factor =1.5*



(b) *Clearing price Comparison between Gen Only and 6 Aggregator case; Gen Factor =0.3;OPXCPXfactor=1; Bal demand Factor =1*

Figure 8-3: Comparison between BAU and a six-aggregator case

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[225] Note imbalance volume factor is shortened to "Bal" and Generation to "Gen" in the figures.

Figure 8-2 b and Figure 8-3 show that the addition of aggregation could result in a reduction in market prices by at least £100/MWh on average. Note with different assumptions on generation and flexibility provision, values change. Less generation would result in a higher BAU CP value, whereas the equivalent six aggregator case would also be higher as aggregator supplied volumes would increase (see Figure 8-3)[226]. It is clear that aggregation will be an important element of a well functioning flexibility market.

8.1.2 Monte-Carlo and Random Elements of the Simulations; Random Seeding

PyEMLab-Agg has been designed to run multiple scenarios (e.g. Monte Carlo simulations) using Python's multi-threading routines[227]. Speed improvement are seen, and results can be stored automatically as the runs progress using this facility. Because the ZIP Trader and propagation modules have a random element to them, that is they use random numbers in their calculations, each run with the same parameters will produce a different output. This means that to fully assess the output of the simulations, multiple runs should be performed (as in Monte-Carlo) and averages or expected values (with percentiles) should be extracted. Because of the long run times (approximately 2-3 hours in a five-year simulation[228]), it would take an inordinate amount of time to perform the simulation shown herein using a Monte-Carlo approach.

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226 Note: It is important that the same generation flexibility assumption is used in the aggregators case in any comparison.

227 Because of Python Global interpreter Lock (GIL), Python is not fully multi-threaded as per Java. Note that potentially blocking operations, such as I/O, image processing, and NumPy calculations, occur *outside* the GIL.

228 Using Alienware 15 R3 7700HQ 2.8Ghz 4 cores 8 logical 32GB DDR4.

A common method to help debug such random simulations is to fix the internal random number generator by providing it with a seed. In this case, the random number generator always produces the same set of random numbers in sequence. As this chapter is seeking to show the various effects of different assumptions, the random seed method has been utilized to aid in comparison without the need to run thousands of simulations.

In the immediately following paragraphs one case is shown (3,000 hours) without random number seeding and is analyzed using 100 runs[229]. Note, parameters are held constant but randomness in the ZIP Trader and social media propagations results in different output for the same parameter settings. It uses the base case assumptions detailed in Appendix K. Figure 8-4 (a) - (b) shows output from 100 stochastic simulations with varying degrees of granularity.

[229] Assuming a normal distribution, an appropriate error level and statistical confidence level, it is possible to estimate the number of simulations required to meet such error conditions [583]. With a 95% confidence limit and an error of £5/MWh, 120 runs would be required. With an error of £1/MWh, 3011 runs would be required. This means that a £15/Mwh change in results could be £10-20/Mwh, as 100 runs would equate to around ~£5/Mwh error.

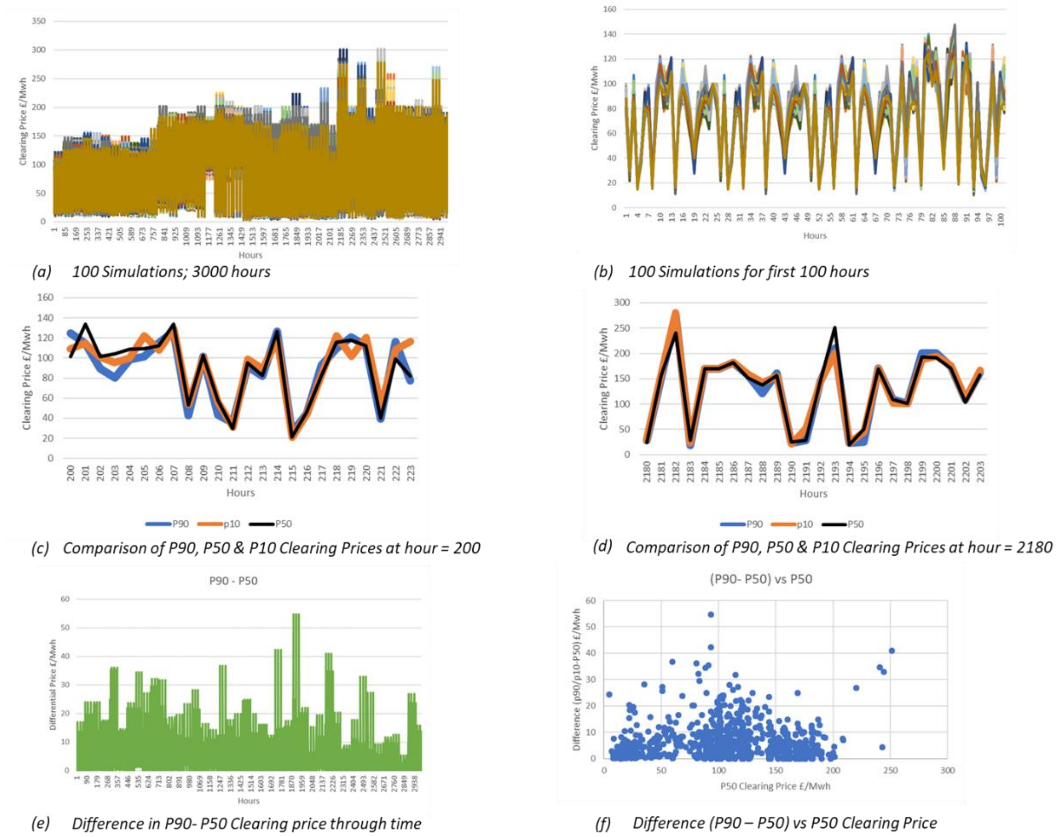


Figure 8-4: The effect of randomness on simulation output; Expected, P90 and P10 evolutions

Using the average CP over the 3,000 hours, the 10th, 50th and 90th percentiles (P10, P50 and P90) have been extracted and are shown at different ticks in Figure 8-4 (c) - (d).

Figure 8-4 (e) - (f) shows the absolute difference between the P90 and P50 values (the magnitude of the random effect) through time and against the P50 value. It is clear from the graphs that for the majority of the time, differences of between £0 -

15/MWh[230] are seen, although in some circumstances much larger values (~£50/MWh) materialise. This is essentially the effect of the randomness in the simulation. Note that there is no correlation between the random element and the average price[231]. Henceforth results shown in the thesis focus on one randomised sequence of numbers[232]. Also note, that to aid in the visualisation of the simulation paths, a 24-hour moving average is shown in most of the figures (unless otherwise stated). Differences in simulation output of less ~£5-15/MWh cannot be assumed to be significant in the following sections as randomness associated with propagation and bidding behaviour could negate these effects.

8.1.3 Tracing the Responses of Key Agents during the Simulation

Statistics for the agents have been collated during the simulation on a weekly and monthly basis. The PyEMLab –Agg framework allows users to easily collect and store matrix style arrays in an hdf5 databases that can be later analysed in MATLAB, R or Excel. Averages and distributions for contract values have also been collected. However, it was found that this did not provide enough granularity to aid in the understanding of model dynamics. Thus, a different approach focusing on key agents was used.

Analysis of the agent social networks outside of the simulation (using a utility written in Python using Network X and SNAP) allowed for the identification of these “key agents”, e.g. the identification of which agents are connected to only a few others

[230] From the average value.

[231] The P50 can be considered the average simulation path.

[232] That is the random numbers have been seeded.

and which are connected to many? The choice of these key agents is summarised below. For example, agent 25923 is initially paired to Aggregator 4 and has four connections to other customers. It has an initial marginal cost of £310/MWh (flexibility up) and £419/MWh down.

Key Agent	Agent Number	Aggregator	Number of Connections	MC up	MC down	Volume up Kw	Volume Down Kw	flex potential	Numbner of Connections	Volumes
1	25923	4	4	310	419	0.01	0.01	0.01	Low	Low
2	25403	1	2	2857	455	0.25	0.01	0.25	Low	Medium
3	1682	3	2	150	150	0.09	1.77	1.77	Low	High
4	18989	1	97	1283	426	0.11	0.01	0.11	Medium	Medium
5	38145	0	42	463	667	0.03	0.01	0.03	Medium	Low
6	27183	4	104	423	309	2.61	2.35	2.61	Medium	High
7	2414	3	1153	370	404	0.08	0.01	0.08	High	Low
8	3887	3	502	29	18	1.15	4.66	4.66	High	High
9	64	2	2404	344	147	0.13	2.2	2.20	High	High

Table 8-2: Summary of nine key agents in the simulations

The simulation environment allows for data on many key agents to be collected, but it was felt that nine key agents was an appropriate number at this stage. Note that post analysis of the social network structure using routines/methods presented in [584-586], may highlight alternative key agents in information cascades. This further analysis of key agents is left for future work.

8.1.4 Short Term and Long Term Simulations

To answer the various question both short term (< 1year) and longer term simulations have been utilized. Short term simulations of 3,000-8,760 ticks (hours) were performed under a number of different parameter settings. In all cases, parameters were varied incrementally so that comparison between cases could be made to provide an insight as to the effect of various key assumptions like social media propagation mechanics, social media network structure and assumptions on Agent Zero weights. Some of those effects are presented in the various subsections and figures below.

During longer timeframe simulations, aggregators can choose to change their business models and change contract offer terms and customers can change contracts many times. The current model will allow aggregators to exit the market and new ones to enter, but this functionality has been disabled in the simulations presented herein. Interested readers are referred to Appendix R for details on these cases. The appendix also includes summary results from the longer term runs.

8.2 Drivers of the Simulation Dynamics: The Significant Parameters

Overall, the dynamics of the simulation in this work depends on a number of variables including the level of flexibility from competing conventional generation, the imbalance volume requirements (flexibility volumes required), the amount of flexibility supplied by domestic and industrial customers, the number of aggregators and so on. There are many variables that can be adjusted; the question is which ones are more important than the others? A standard approach used in the social sciences and econometrics is to statistically analyse the drivers for statistical significance using techniques like multilinear regression. The standardized beta provides a measure of how important one variable is compared to another, and the significance measure provides the researcher with a clue as to whether the variable is important or not. Additionally a linear model derived from complex simulations can be extremely helpful in understanding such a model as well as aiding in validation. This technique been used little in ABM, but as will be shown – provides useful insights into this complex simulation. Note other approaches such as Sobol analysis could have been used.

8.2.1 Batch Runs: Parameter Sweep

PyEMLab-Agg was modified to take parameter values from a CSV file and run multiple cases under different parameters. Parameters were changed randomly between the ranges shown in Table 8-3 and forms the input for a statistical analysis.

Parmeter	Base Factor	Min range	Max Range
Balancing demand Factor	1	0.2	2
Generator Demand Factor	0.4	0	1
Domestic customer flex factor	1	0.5	2
Domestic trader agent zero learning factor	0.5	0.1	1
Aggregator agent trader learning factor	0.5	0.1	1
Message Receive probability	0.3	0.2	1
Domestic bid prices % higher	1	1	2
Agg OPX/CPX Factor	0.4	0.4	1
Risk hedge on =1	variable [0,1]	0	1
Starting margin%	50%	30%	90%
Start fixed price offer £/Mwh	50	20	125
Start contract type	variable [0,1,2]	0	2
Freq of Congestion	1	1	2
Expecations £/Yr	10	0	150
Number of Aggregators	6	1	6
# of Domestic customers	50,000	30,000	50,000
# of Industrial customers	4500	1,000	4,500
# of Aggregator Buckets	6	1	10
Dom agent zero learning fac	0.1	0.1	1
AZ wt V	0.333	0	1
AZ wt P	0.333	0	1
AZ wt S	0.333	0	1
Stimulus to AZ input ratio	1:1	1:1	5:1
Aggregrator Update Frequency - Target Price	Daily	Daily	3 monthly

- number
AZ - Agent Zero
Wt - Weight

CPX/OPX - Operating Capital costs

Table 8-3: Parameters used in batch runs for simulating short term dynamics

In this case, around 300 runs[233], over 3,000 ticks/hours were collated and later analysed using SPSS 25 [194, 587-589]. The key element of this analysis was to highlight the significant drivers in the simulation for key output variables including clearing price (CP), Hurst exponents (an indicator of simulation dynamics), aggregator profits, customer revenues, and Agent_Zero average scores (V, P, S,D). Such analysis could also be used to create simpler models of the process currently being simulated, but care should be taken with this simplification as the equations derived depends on the input data used in the simulation.

To facilitate an initial analysis, a multilinear regression has been performed. The system is clearly non-linear so a linear approximation may be inappropriate in some cases. However, a multilinear regression analysis is easier to interpret than a more complicated nonlinear one. Note that in some instances the adjusted R^2 for linear representations is low (of the order of 0.3-0.4), indicating that the model is not a good fit in these cases. Note the Sobol method could have been used to identify important variables (See [590, 591] for its use) and is useful in highlighting potential non-linear relationships. In addition, a brief review of the non-linear nature of the simulations was investigated using a multi-layer Neural Net (NN). An approximation function was used to train and test the simulation data output using a 21-parameter input layer, 1 hidden layer and an output layer with a single output (e.g. clearing price, HHI etc.), as an initial set up. The network was trained using a using a feedforward static back

[233] Using the method set out in [583], with a 95% confidence limit, 300 runs would result in an error of ~ £3.2/MWh.

propagation approach and a sigmoid transfer function was used in each neuron. The software package NeuroSolutions 5 for Excel [592, 593] was used to create this network and its sensitivity testing around the mean feature [594, 595] to highlight relationships between input variables and their output variable. The cross validation error of the trained network was 0.0279. Significant driver variables were found to be similar to the linear analysis, although the NN highlighted the use of more input variables for the HHI output, in particular. Some variables were found to be non-linear exhibiting $X^{2,}$ X^3, natural log or exponential non-linear functions rather than linear functions. It is likely that a non-linear model would provide better results, although a detailed analysis was left for a future date.

8.2.2 Key Drivers of Clearing Price (CP) and other Variables

Figure 8-5 -Figure 8-7 summarizes the multilinear analysis from SPSS, for 300 short term simulations for different output variables. Figure 8-5 and Figure 8-6 uses standardized betas to allow comparison between variables to identify the relative importance. Only those variables that were significant are shown.

Standardized Betas

	Adjusted R^2	Bal demand Fac	Gen Demand	Number of Aggregators	Dom customer flex	# of ind customers	Number of buckets Agg	agg agent trader learning fac	start fp	Risk Hedge On	agent wt P	Agent wt S	Rx Prob	Expectation £/yr	Dom agent zero learning fac	Start Margin
CP	0.723	0.61	-0.46	-0.34	-0.23	-0.09										
Hurst	0.438	0.56	0.28		-0.18		-0.17	-0.16								
Vol%	0.346	0.52	-0.25						-0.16							
HHI	0.718			-0.85												
Agg Profits	0.481	0.31	-0.15				0.13			0.56						
Cust Revs	0.228						-0.35			0.37						
Agg 4 P-S	0.307	0.24	-0.22		0.13						0.17		0.40	-0.14		
Agg1 V-S	0.528										0.48	-0.24	-0.42		0.33	
Avg V	0.71	0.53	-0.25		-0.17		-0.11		0.21				-0.45	-0.39	0.14	-0.10
Avg D	0.695	0.58	-0.28		-0.16		-0.09		0.21				-0.37	-0.39		-0.09
Max D	0.688	0.59	-0.26	0.24	-0.15				0.17				-0.32	-0.36		-0.09
Max V	0.688	0.56	-0.21	0.23	-0.18		-0.12		0.21				-0.36	-0.39	0.10	

Figure 8-5: Standardized betas for simulation parameters

Averages for all customers Agent_Zero values (D,V,S,P) were calculated, as were the max values for D and V. The difference in average scores between V and S for aggregator 1; and P and S for aggregator 4 are also provided.[234]

Importance

	Bal demand Fac	Gen Demand	Number of Aggregators	Dom customer flex	# of ind customers	Number of buckets Agg	agg agent trader learning fac	start fp	Risk Hedge On	agent wt P	agent wt S	Rx Prob	Expectation	Dom agent zero learning fac	Start Margin
CP	35%	27%	20%	13%	5%										
Hurst	42%	21%		13%		12%	12%								
Vol%	56%	27%						18%							
HHI			100%												
Agg Profits	27%	13%				12%			48%						
Cust Revs						49%			51%						
Agg 4 P-S	18%	17%		10%						13%		30%	11%		
Agg1 V-S										33%	17%	28%		22%	
Avg V	22%	10%		7%		5%		9%				19%	17%	6%	4%
Avg D	26%	13%		7%		4%		10%				17%	18%		4%
Max D	27%	12%	11%	7%				8%				15%	17%		4%
Max V	24%	9%	10%	8%		5%		9%				15%	17%	4%	

Figure 8-6: Importance ratios for simulation parameters

In terms of average clearing prices (CP), only five parameters are seen as important in explaining the average CP in the short term[235]. As expected Agent_Zero (AZ) values (V,P,S,D) depend upon other variables such as customer expectations, receive probabilities and AZ learning factors.

Figure 8-7 presents generated linear equation coefficients, and constants.

Coefficients

	Constant	Bal demand Fac	Gen Demand	Number of Aggregators	Dom customer flex	# of ind customers	Number of buckets Agg	agg agent trader learning fac	start fp	Risk Hedge On	agent wt P	agent wt S	Rx Prob	Expectation	Dom agent zero learning fac	Start Margin
CP	972.73	493.45	-662.14	-100.01	-226.74	-0.03										
Hurst	0.40	0.14	-0.08		-0.05		0.01	-0.08								
Vol%	77.88	46.38	-40.36						-0.26							
HHI	7131.00			-1035.32												
Agg Profits	-158.26	146.26	-131.43				12.95			297.46						
Cust Revs	107.96						-20.22			119.69						
Agg4 P-S	-0.10	0.04	-0.06		0.02						0.07		0.14	-0.0003		
Agg1 V-S	0.01										0.13	-0.08	-0.10			
Average V	-0.40	0.20	-0.16		-0.08		-0.01		0.0014				-0.39	-0.0018	0.11	-0.11
Average D	-0.43	0.21	-0.18		-0.07		-0.01		0.0013				-0.31	-0.0018		-0.09
Max D		0.26	-0.21	0.04	-0.08				0.0014				-0.33	-0.0020		-0.12
Max V	-0.53	0.26	-0.17	0.04	-0.10		-0.01		0.0017				-0.38	-0.0022	0.10	

Figure 8-7: Linear regression equations (Coefficients) for simulation parameter

Visualisation of these complex relationships provides a useful mechanism to both validate and understand relationships and are considered useful tools for engaging

[234] These aggregators show the greatest difference.

[235] In the longer-term, other factors appear to come into play when message propagation takes effect.

with stakeholders [596, 597]. Linearization is one method to simplify such relationships. Fuzzy Cognitive Maps (see section 8.8), or causal mapping in general is another useful tool and, of course, the two can be combined.[236]

As part of this work, a linear based visualisation tool has been created (Figure 8-8)[237].

Figure 8-8: Flash based software based on linear regressions of simulations

The tool allows users to adjust assumptions using the sliders on the rhs of the application and to see the effect on key performance indicators.

8.3 General Simulation Questions

The first two questions in Table 8-1, have been answered in section 8.2.2 and the

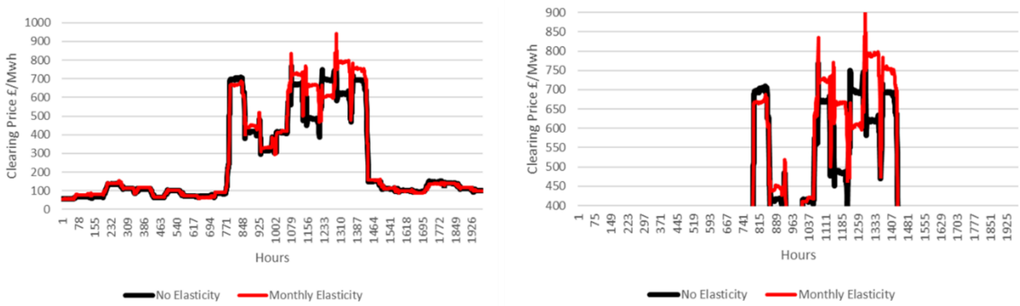
[236] The linear relationships can be used to parameterize FCM models.

[237] See https://github.com/Ghoworth/Aggregator-Simulator-flash-

rest that associated with general issues (questions 3-5) are now answered in this section using simulation results from the PyEMLab framework. Note these are initial views of the questions[238].

8.3.1 The Effect of Demand Elasticity on Clearing Price

Demand for flexibility services were initially fixed in the simulations, but one might expect that flexibility might change according to price levels. Flexibility levels are typically related to overall demand and demand would be expected to be price elastic to some degree. The current model allows both monthly and yearly elasticity adjustments to demand and therefore flexibility volumes. An elasticity value of -0.07 has been used for monthly and -0.3 for yearly values (as per discussion in section 2.4.1). Figure 8-9 shows the effect of including elasticity on the evolution of clearing prices.



(a) Effect of Elasticity *(b) As (a) but with Truncated Y axis*

Figure 8-9: Effect of short-term demand elasticity on clearing prices

With the elasticity effect switched on, overall demand and hence flexibility requirements are adjusted according to the change in monthly clearing price values.

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[238] Additional simulation work maybe required to fully answer some of these questions. This is for future work.

The simulations in the short term show that when prices are low, the effects of elasticity are small and when clearing prices are more than £400/MWh, short term elasticity effects can result in differences of £100-350/MWh, which is significant. However, the average price differences between the two curves is £22/MWh (~9% of average prices) with a slight difference in price volatilities, which may be undiscernible from other random effects due to bidding and message propagation.

In the case of short term outages like the Texas blackouts in 2021, elasticity effects would be expected to be substantial, but only in the short term i.e. a few months. During the period of these outages in Texas, wholesale electric prices were set to $9,000/megawatt-hour (the "system cap" set by ERCOT), compared to a more typical $25/MWh [598]. Because prices remained high for a week or so, the elasticity model used in the simulation would suggest that demand would reduce by >500% in the following month which of course would be ridiculous. Where outages are for less than a day then the current model performs much better with an expected 3% reduction in demand the following month.

In the case of longer term price impacts like the Ukraine war – where prices have remained high for over a year (more than doubling) in the UK – it would appear that the elasticity model would suggest a 30% reduction. UK Electricity demand grew in the period 2021 -2021 but the demand base had been reduced because of COVID19. It is difficult without isolating the various effects to determine whether the elasticity model reflects reality. It is clear, however, that further work is required to properly address these elasticity effects.

8.3.2 Impact of Bidding Behaviours and Contract Type on Price Evolution

Figure 8-10 shows short-term price evolution for simulations using different starting contract conditions. In the base simulations, customers are started with a random selection of contracts types (labelled as "all contracts" in the figures). For illustration, the figures below show comparisons with a starting position based on contract type 2 (fixed prices). Note there is no generation flexibility competing with the aggregators in some cases.

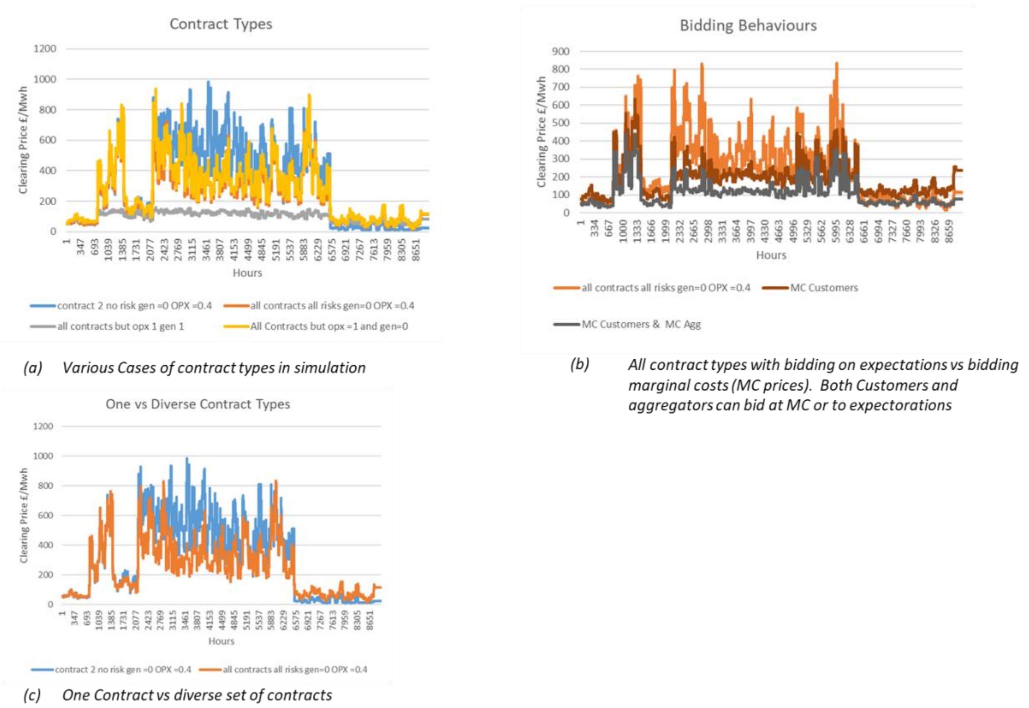


Figure 8-10: Impact of contract and bidding behaviours on long-term price evolution

Significant price differences can be seen between having a diverse set of contracts at the start of the simulation and having just one (Figure 8-10 (c)). It is also clear that if aggregators and customers bid to their marginal costs (Figure 8-10 (b)), then clearing prices would be at their lowest. In addition, the marginal cost model shown takes no account of the operating and capital cost of the aggregator. The model just passes on the marginal cost (MC) of the bucket to the clearing market. As shown in prior sections this could equate to a value of around £200/MWh. The MC modelling also results in clearing prices that are less volatile. This result suggests that in an ideal (perfectly competitive) world, both customers and aggregators should bid to their marginal costs. However, in practice real market participants behave differently, more strategically and customers that see prices at £500/MWh are not going to bid in at their marginal cost of supply at £30/MWh for very long. In addition, domestic customers are not likely to fully understand the true marginal costs of the flexibility that they are providing and emotions will play a part.

8.3.3 How do the Long Term Dynamics change?: Hurst Exponent Evolution

Plots of the Hurst coefficients[239] for the same simulations over a timeframe of five years are presented in Figure 8-11. It is clear that different dynamics are exemplified in the Hurst coefficients, as for example in cases 13, 5, 10, and 6. Note the long term cases are described in Appendix R.

[239] See section 7.1.5 for a description of the use of Hurst coefficients/exponents.

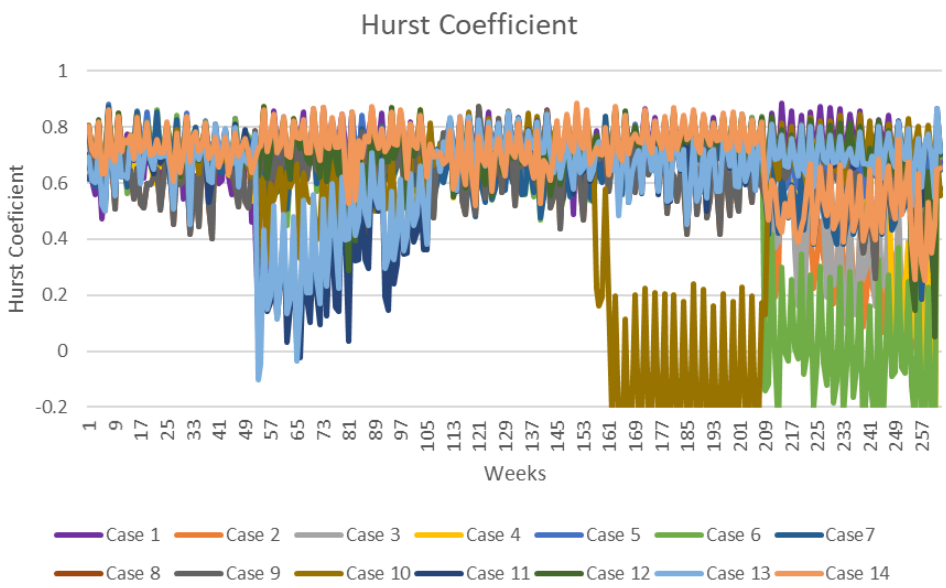


Figure 8-11: Hurst coefficient for different simulation across 5 years

Generally, other cases remain in the 0.6 - 0.8 range meaning that they have strong trends either up or down over the period. Cases 13 and 11 gravitate towards a Hurst coefficient ≈ 0.1-0.2 after the first year, but return to the 0.6-0.8 range after a year or so. The step changes in dynamics at week 161 and 209 for case 10 and 6 respectively would be interesting to investigate further but this is currently beyond the scope of this thesis.

Case 14 in the last year (week 208+) hovers in the geometric Brownian motion region (Hurst ≈ 0.5), whereas case 10 and 6 gravitate to a mean reverting stable region (near zero).

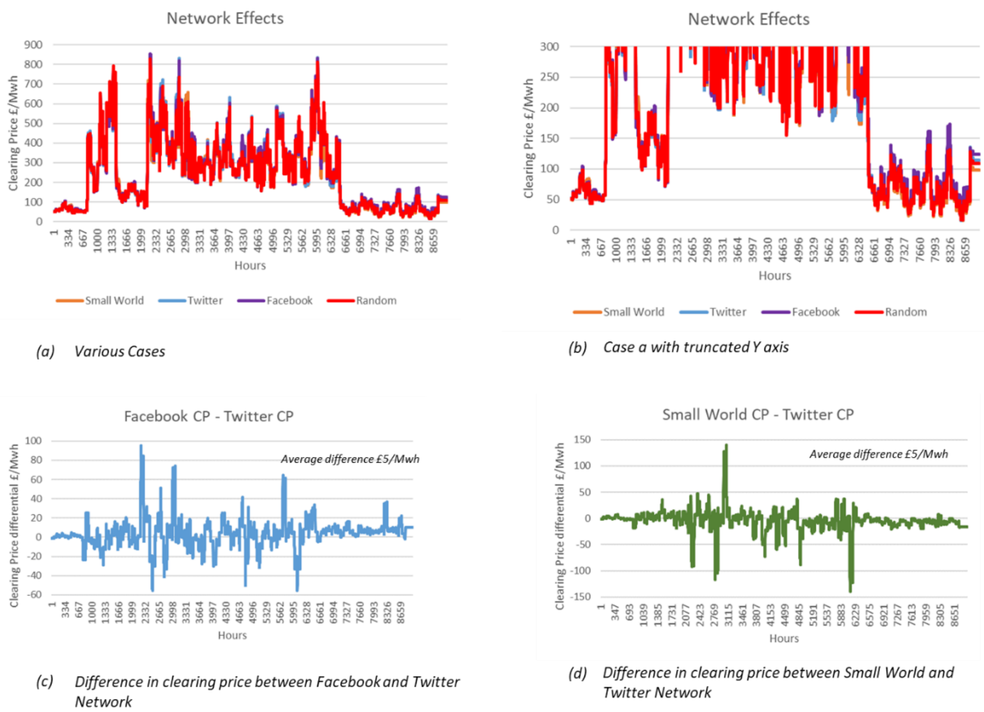
It is clear that the dynamics of the simulation are changing in some of the cases, and can only be seen when comparing across years and highlights the issue of looking only at one particular year.

8.4 Social Network Simulation Questions

This section provides results for simulations associated Social Network interaction questions 6 - 7 in Table 8-1.

8.4.1 Network Structure: Social Interactions

The effect on simulation clearing price for the different types of network structures (discussed in section 6.3) are shown in Figure 8-12.



(a) Various Cases

(b) Case a with truncated Y axis

(c) Difference in clearing price between Facebook and Twitter Network

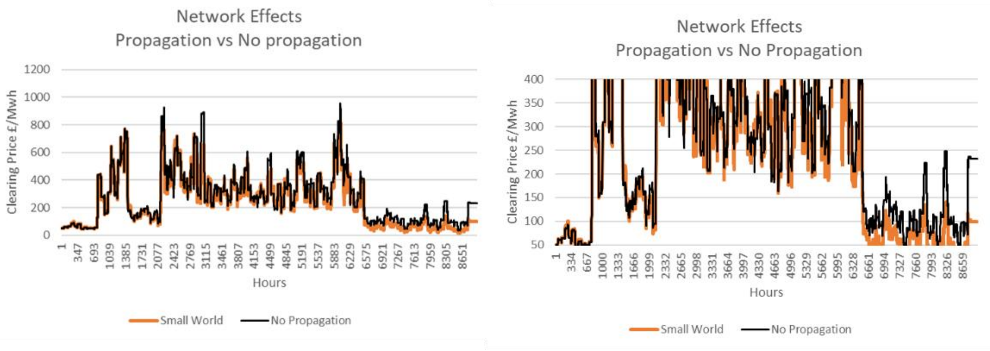
(d) Difference in clearing price between Small World and Twitter Network

Figure 8-12: Short-term network effects on clearing prices

Figure 8-12 (c) – (d) provides a more clearer view of the differences associated with different network structures, by concentrating on the price differences using the Twitter network as a base case. For much of the time small differences are seen in short term clearing price evolution (less than £10/MWh), but large differences can occur as spikes (£60-140/MWh). Note large differences would only be expected to occur when message propagation amongst a number of agents occurs, and the specific social network structure, e.g. Twitter or Facebook, will be important in determining the value and frequency of these spikes.

8.4.2 Propagation (On or Off): The Effect of Customer Messaging

Short-term propagation effects (one year) on clearing prices are shown, using a simulation without a social media network and a randomly generated small world network with p=0.01[240] (Figure 8-13). Note that in Figure 8-13 (b) the Y-axis has been truncated at £400/MWh.



(a) Small world Network Vs No Propagation (b) Case a with truncated Y scale

Figure 8-13: Effect of propagation on clearing prices; Short-term

Propagation reduces prices by around £30/MWh over the year but differences can be as large as £100/MWh. Larger differences can be seen when the model is evolved over 5 years.

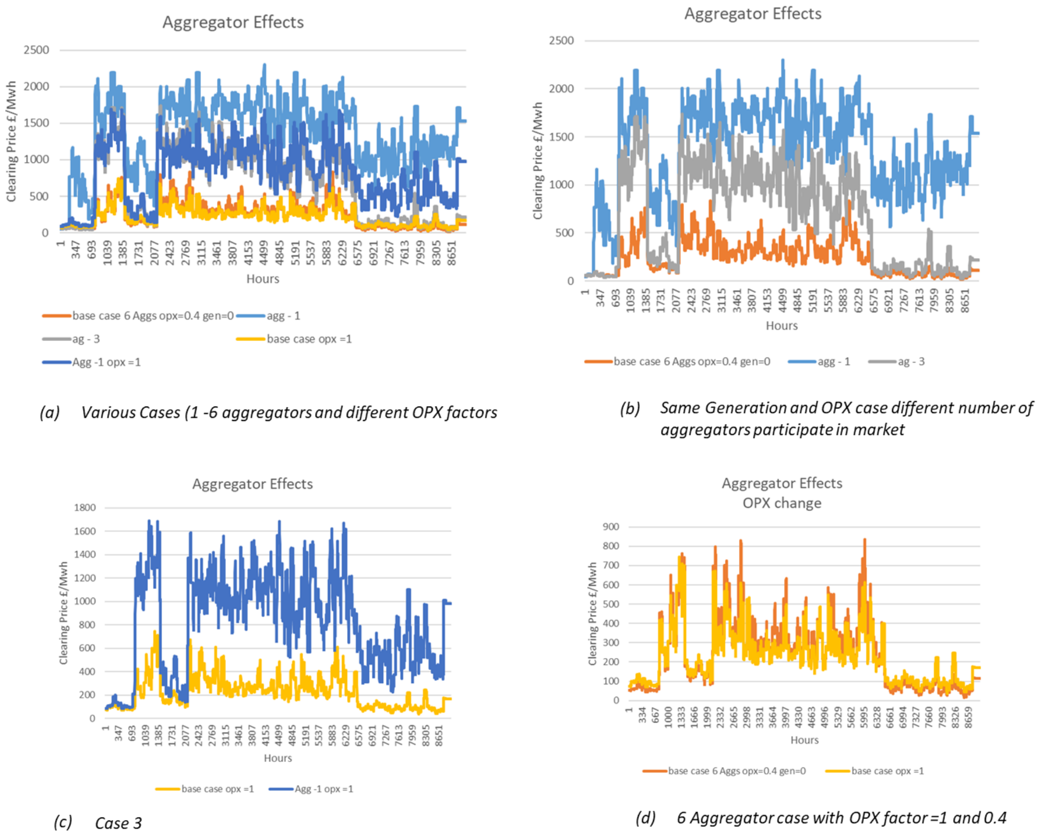
8.5 Aggregator Simulation Questions

This section provides results for simulations associated with Aggregator interaction questions 8 - 15 in Table 8 1.

[240] Note p is the probability that a link will be formed between two nodes.

8.5.1 Competition: The Effect of Aggregator Numbers

The short-term effect of aggregator numbers on clearing prices is shown in Figure 8-14. The base case assumes six aggregators competing with each other, both in providing bids and in attracting customers to their business. The graphs also show some effects from changes in aggregator operating costs[241]. All cases in this figure has generation flexibility set to zero, so that the effect of aggregator numbers can be more clearly seen.



(a) Various Cases (1 -6 aggregators and different OPX factors

(b) Same Generation and OPX case different number of aggregators participate in market

(c) Case 3

(d) 6 Aggregator case with OPX factor=1 and 0.4

Figure 8-14: Effect of aggregator numbers on clearing prices

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[241] Labelled as OPX in the figures.

Note that in the case where there is no competition from generators providing flexibility[242], one aggregator results in very high clearing prices (4-5 times higher). This is obviously not a desirable case. The simulation is designed to optimise aggregator profits, so if aggregators remain unchecked, they will raise prices excessively as they have a monopoly. This changes when there is more than one aggregator. As will be shown later 4-6 aggregators (section 8.7) will be required to provide adequate benefits to customers in a potential flexibility market.

8.5.2 Bucketing Approach by Aggregator

The bucketing algorithm for the submission of bids will form an important element of the profit model of an aggregator. Optimisation of such profits will take place in the face of uncertain prices, volumes and risk. Section 7.2.1 and Appendix N presented the bucketing algorithms used in this thesis. Aggregators in this simulation use four algorithms to simulate the effects of different bucketing strategies e.g. equal ranges, equal number of bids in each bucket, equal volumes and the AstroPy heuristic (section 7.2.2). A genetic algorithm approach was considered, but computational run times would have been increased. Figure 8-15 shows aggregator profits over 80 days, for the various strategies. One of the cases shown, shows a sensitivity based on using five buckets rather that the ten used in the majority of the cases.

[242] Gen factor=0.

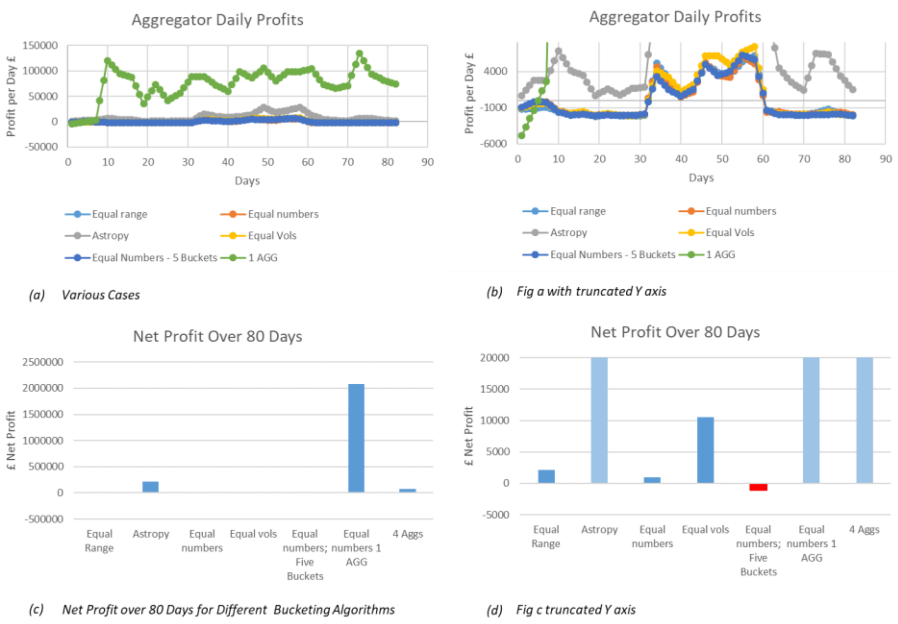


Figure 8-15: Aggregator bucketing algorithm affects profits

Note that in Figure 8-15 (a) and (c) the Y-axis has been truncated at £4,000 and £20,000 respectively to highlight the differences in smaller value cases. Note that in all cases other than the "1 AGG" [243], six aggregators have been used in the simulation. For the 6-aggregator cases, it is clear that the AstroPy bucketing algorithm provides the best aggregator profitability with clearing prices commensurately high.

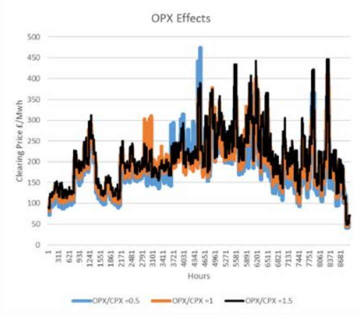
8.5.3 The Effect of Costs on Clearing Prices

Aggregator operating and capital costs are a key assumption within the model, as aggregators will need to cover such costs in order to make a profit. Aggregators adjust bids in the face of competition from generators and other aggregators. Figure 8-16 shows the effect of costs on the clearing price output under different cost assumptions.

Sensitivity cost factors are used to multiply base cost assumptions presented in

[243] 1 AGG = One Aggregator.

section 4.3 (e.g. 1, 1.5 and 0.5 times the base cost).

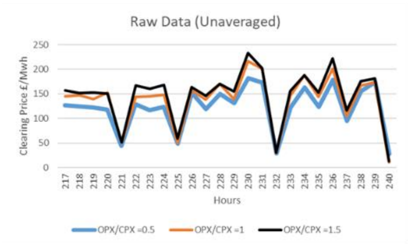


(a) Impact of Aggregator Operating (24 hr moving average)

	OPX/CPX =0.5	OPX/CPX =1	OPX/CPX =1.5
P90	283	296	322
P10	19	22	26
Average	180	192	206
Abs STD	192	203	222
Volatility	107%	106%	107%

CP /CP avg	0.94	1.00	1.08
CP /CP P90	0.95	1.00	1.09

(b) Comparison of Yearly averages, P10, P90 Values



(c) 24 Hours of Raw Un-averaged data

Figure 8-16: Effect of aggregator costs on clearing prices

Cost impacts on prices are not linear, and a 50% increase/decrease in operating costs is not reflected either in the up or down price movements. Section 4.3.1 indicated that breakeven costs for the aggregator with 6,000 domestic customers was of the order of £100/MWh but this assumed that volumes are much higher than those seen in the simulation. We would, therefore, expect simulation prices to go up and down on average by at least £50/MWh, but they did not. However, as long as prices cover the operating and capital costs, prices do not need to rise as much as this, and competition amongst aggregators will help to dampen any unnecessary increases.

8.5.4 Aggregator Contract Starting Positions and its Impact on Clearing Prices

Section 8.3.2 showed the effect of customer contracts on clearing price evolution. This section deals specifically with the aggregators and their contract offers to the market. Figure 8-17 shows the impact of different contracts on the market dynamics. Aggregators are given their starting contract position (including risk stance) via a CSV input file. This CSV file assigns different contract types[244] to the domestic customers randomly and these customers are assigned to an aggregator. The aggregator therefore has a portfolio of different contract types i.e. contracts 0-2. The "all aggs diff"[245] line in the graph below reflects the case where the aggregator has a mix of contract types and in this scenario has risk management enabled, whereas the "all-risk off" reflects the same inputs but without risk management. In the case of the "contract 0", "contract 1", and contract 2" lines, the aggregator contract portfolio is assumed to be all of the same type e.g. "Contract 1" etc.

[244] Revenue business models (section 4.2.7) define the contract types. Contract 0 - pay as clear %, Contract 1 – pay as bid and Contract 2 – Pay fixed price

[245] Short for all aggregator starting inputs different.

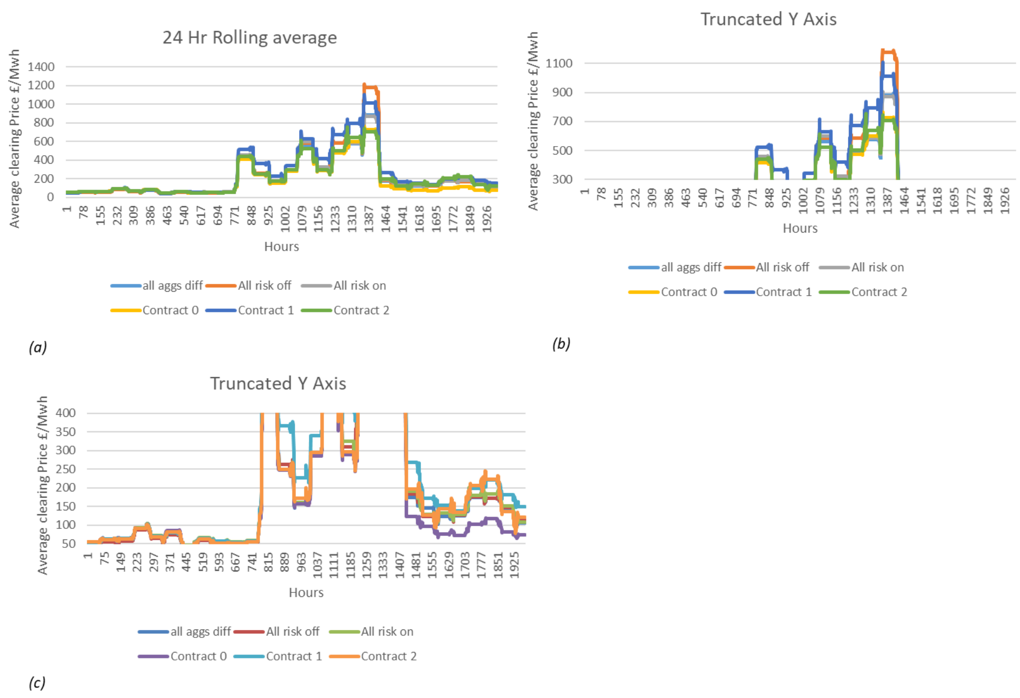


Figure 8-17: Short-term simulation of six aggregators with various starting conditions

The overall shape of the simulations are obviously driven by imbalance volume assumptions[246], but the starting positions of the aggregators (in terms of risk approach and contract type), clearly have a significant impact on clearing prices e.g. £200-£500/MWh difference.

8.5.5 Aggregator Selection by Customers

Each agent can select one of six aggregators, numbered 0-5 during the simulation. Aggregators can change business models yearly, but change terms monthly. A number of contracts expire each month and are renegotiated. Essentially aggregators are locked into a contract type (with or without risk management) for the year, but can change the parameters associated with the contract type monthly. Figure 8-18 shows how the aggregator business model choices change through time for four different cases

[246] This is an input.

of note for two key agents.

Key agent 6 changes its contracts at the end of March and agent 8, at the end of December.

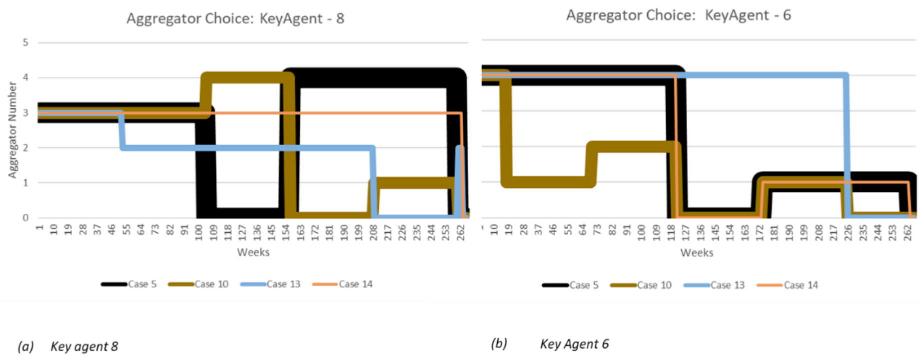


Figure 8-18: Aggregator choice by case through time for two key agents

For example in case 10[247], key agent 8 changes its aggregator many times and contracts with 4 different entities over 5 years. It appears that the agent with the most connections, lowest MC and highest flexibility volumes is more volatile in its choice of aggregators over time, but care should be taken with this conclusion. Future work should focus on aggregator changes, because frequent changes, may be bad for aggregator performance and consumer confidence.

8.5.6 Number of Customers: Evolution Through time

Collation of the customers by various types allows consideration of market performance. Figure 8-19 shows the evolution of market share for the six aggregators modelled through time, and Figure 8-20 uses market share data to calculate the HHI[248] index for the market through time for a variety of cases set out in Table R-1 in

[247] See Appendix R for a description of the long-term cases.

[248] See section 7.1.5 for description of HHI.

Appendix R.

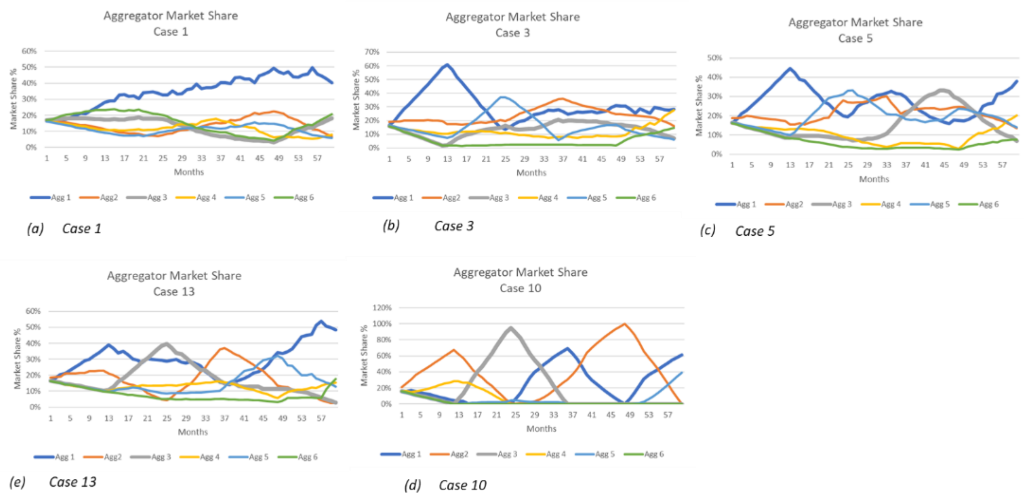


Figure 8-19: Market share evolution across four scenarios

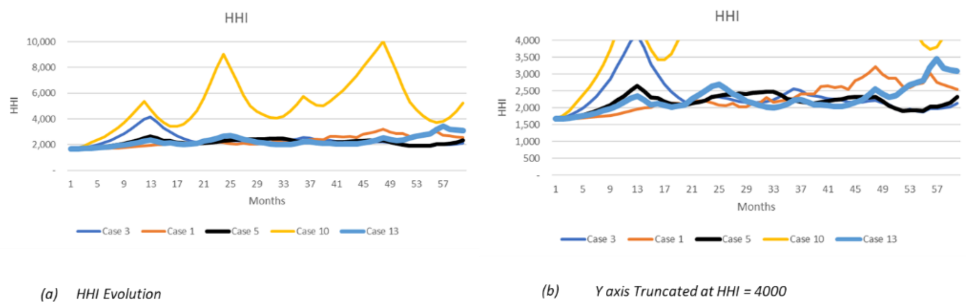


Figure 8-20: HHI evolution across four scenarios

Case 10[249] shows some unusual market share trends with one aggregator dominating, then another, and the HHI levels would be unacceptable to regulators in the UK and USA[250]. In cases 1, 3, 5, and 10, aggregator 6 drops to near zero market

[249] See Appendix R for a description of the long-term cases.

[250] Requirement of HHI of 2,000 and 2,500 respectively.

share and at this level, the aggregator would find it hard to turn a profit. Note in prior analysis it was shown that aggregators would need around 6,000 domestic customers to breakeven[251], so aggregator 6 would probably leave the market after a few years of low market shares. This would affect future model evolutionary output.

8.5.7 Contract Type Market Share Evolution

Figure 8-21 extends the analysis on market share and categorizes the output by contract type for a selection of cases (with propagation via social networks) and a "no propagation" case[252].

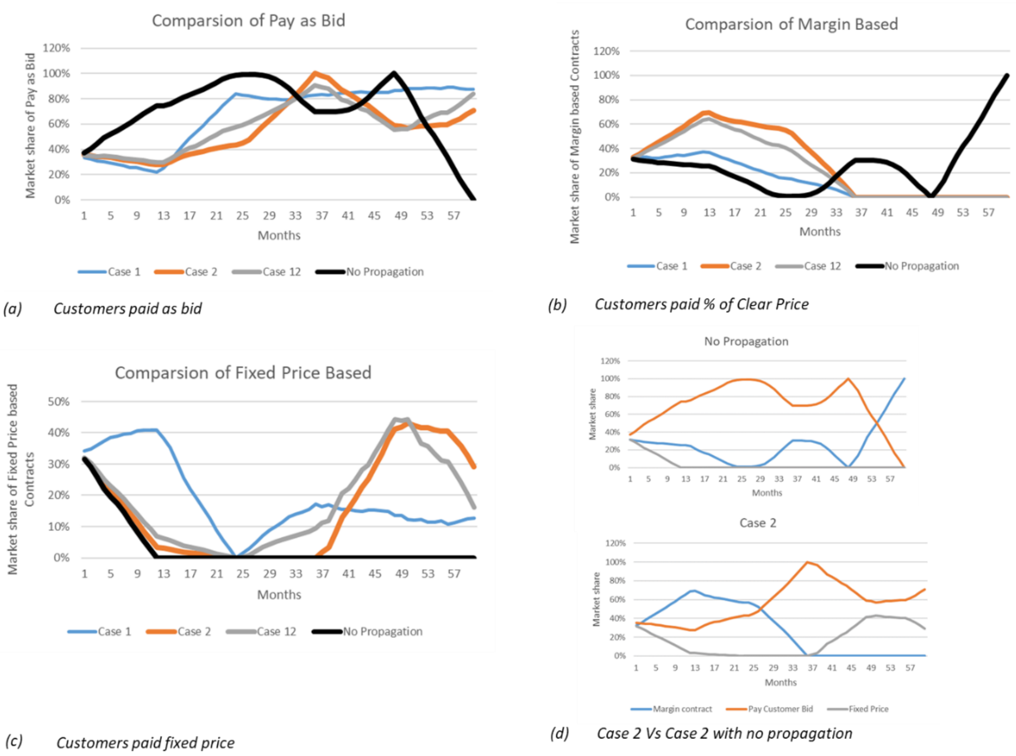


Figure 8-21: Market share by contract type

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[251] Assuming 700 or so Industrial customers.

[252] For case 2.

Figure 8-21(d) provides a comparison of all contract types over the 5 years of simulation. There is clearly a different response to preferred contracts with and without propagation dynamics. The "pay customers as bid" contract is generally preferred in this example, but this may be a function of the starting margin selected in the simulation.

8.5.8 Aggregator Business Model Evolution

Aggregators in this simulation are provided with a starting business model (BM) numbered 0 – 5. The first three BM's (0 - 2 inclusive) do not include risk management whereas the last three (3-5) include it[253]. The cost of operating such business models depends on how many customers have joined up with a specific aggregator[254] and whether the business model includes a risk management function. To switch from a non-risk management to a risk management stance, requires an one-off investment of £0.5 million pounds[255].

Figure 8-22 shows how the BM's change through time at the end of each year. A selection of aggregators and case studies are shown for brevity. The simulations so far indicate that aggregators do not wish to switch between a risk management one and a non-risk management one. It is not exactly clear why this happens, but it is probably because the cost of switching is too high and also because aggregators change contract conditions to limit losses associated with the simulation. This requires further investigation but will be considered in future work.

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[253] These are related to the scheme numbers 1-6 presented in section 4.2.6.

[254] See section 4.1.5 for variation of costs with customer numbers.

[255] Assumption based on authors experience in a risk management organization and with discussions with industry contacts.

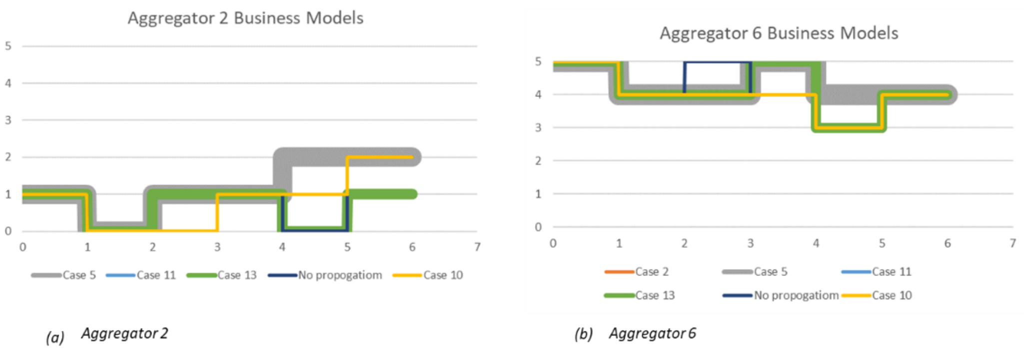


Figure 8-22: Business model selection evolution

Although it is not shown, aggregator 1 in case 1 does not change from its initial, business model throughout the simulation.

8.5.9 Aggregator Risk

The evolution of risk for three aggregators is shown in Figure 8-23. The figure shows risk premia expressed in £/MWh over the 5 year simulation for various cases. Risk premium for the aggregators are relatively high, much higher than were expected from the initial analysis presented in Chapter 5. On reflection and with inspection of the results, this is because the CP volatilities are around 90-150% in the actual simulation whereas the analysis presented in Chapter 5 uses volatilities in the region of 20-40%. In addition, option exercise prices are also different in the simulation.

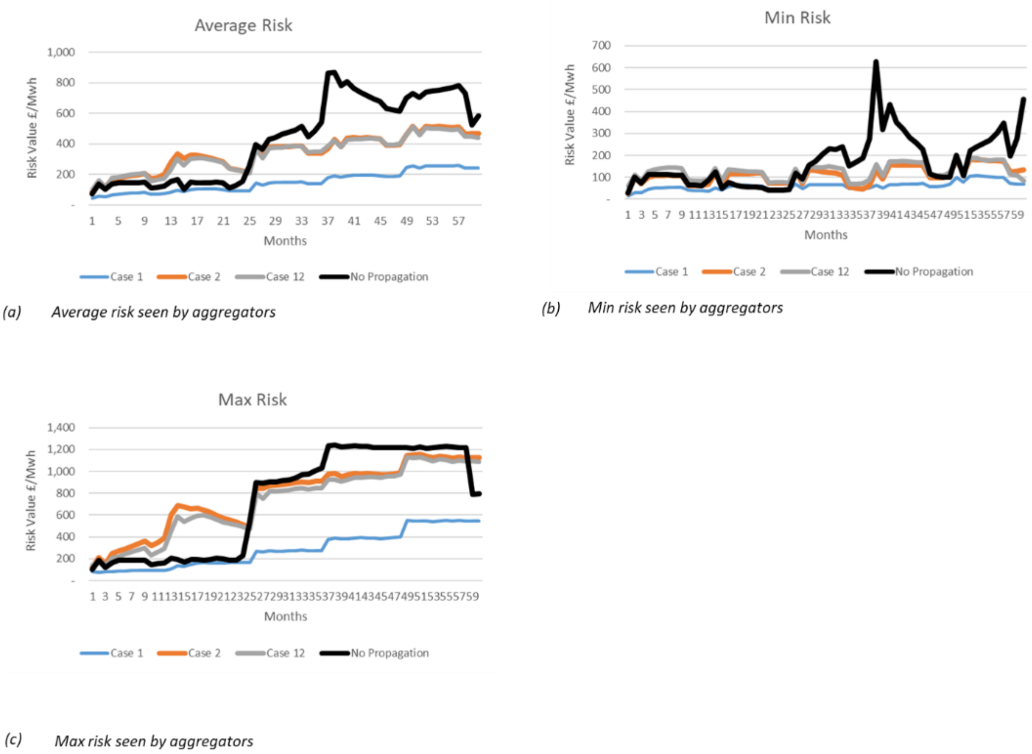


Figure 8-23: Risk evolution for various cases

As aggregators lose customers, target bid prices to cover operating and capital costs increase. This impacts on exercise price[256] which in turn increases option or risk value. The minimum risk of all the aggregators (Figure 8-23 (b)) represents the risk associated with the aggregators with the most customers and also the best profits. The maximum risk (Figure 8-23 (c)) is associated with the worst performers. Social networking appears to help in reducing risk in certain aggregators (Figure 8-23 (b)); cases with propagation vs no propagation). In the case where social network accelerates loss of customers, risk would be expected to be higher (Figure 8-23 (c)).

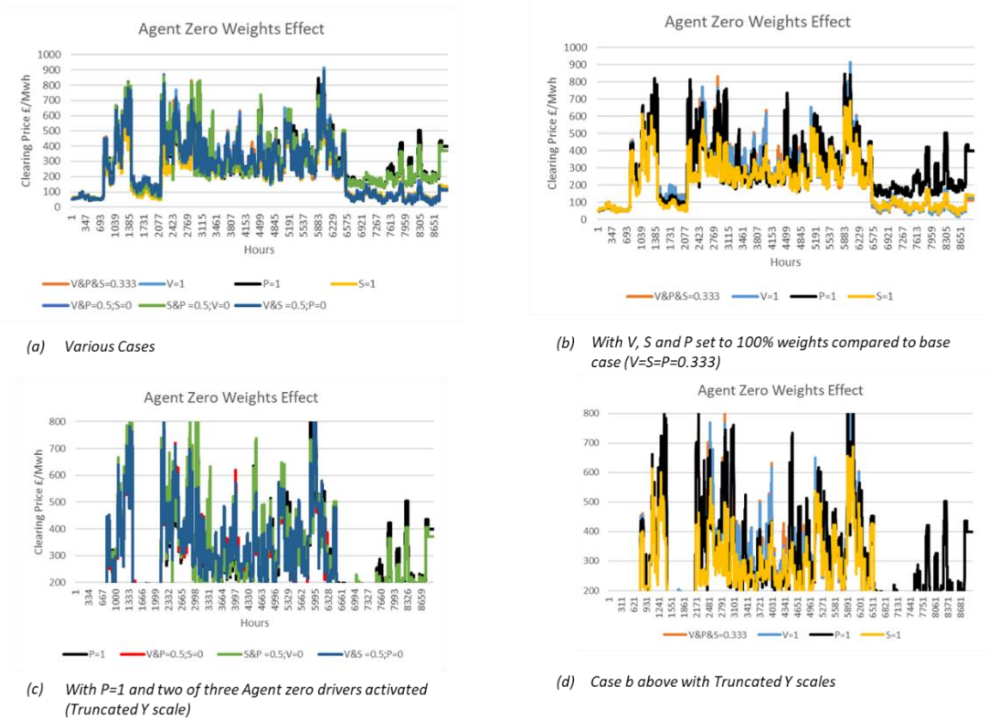
[256] The target price is the exercise price.

8.6 Agent_Zero Simulation Questions

This section provides results for simulations associated with the last two questions in Table 8-1. These pertain to how Agent_Zero assumptions affect the simulations.

8.6.1 Agent_Zero Weights

The Agent Zero model in this simulation uses a base dispositional score D which is a weighted average of V, S, P, as discussed in section 6.4. The base case uses equal weights set at 1/3. Sensitivities using different weights e.g. V_{wt}=1 P_{wt}=0, S_{wt}=0, and so on, have been performed and the results for clearing price evolution for one year is shown in Figure 8-24 and summarized in Table 8-4.



(a) Various Cases

(b) With V, S and P set to 100% weights compared to base case (V=S=P=0.333)

(c) With P=1 and two of three Agent zero drivers activated (Truncated Y scale)

(d) Case b above with Truncated Y scales

Figure 8-24: Effect of Agent_Zero weights

	V&P&S=0.333	V=1	P=1	S=1	V&P=0.5;S=0	S&P =0.5;V=0	V&S =0.5;P=0
P90	498.5	525.0	494.4	413.5	478.8	502.8	528.7
P10	8.5	8.2	23.0	11.4	9.1	22.1	8.0
Average	246.4	254.5	290.6	210.5	250.4	291.2	248.8
Absolute Volatility	441.9	453.3	456.7	355.9	447.5	454.8	447.5
% Volatility	179.4%	178.1%	157.1%	169.1%	178.7%	156.2%	179.9%

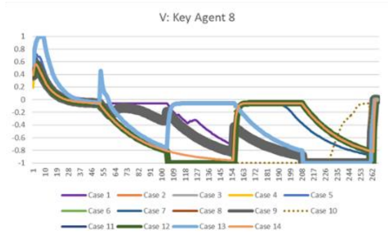
Table 8-4: Summary statistics; Effect of Agent_Zero weights

Results show that differences in clearing prices can occur with different assumptions in Agent_Zero weights. The differences can be greater than those for network structure effects alone. The assumption that all agents have the same weighting is obviously an artificial one, but without actual data, provides a good starting point. Interestingly if all agents based their decision solely on social scores then clearing prices would be some 15% lower than the cases where weights are apportioned evenly (V=S=P=0.333). In a production model of this simulation it will be important to calibrate customer weights once appropriate data is acquired.

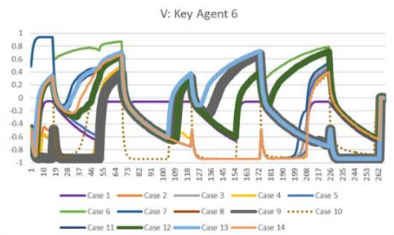
8.6.2 Long-term Impact on Evolution of Agent_Zero Values

Collection of data for key agents (section 8.1.3) in the simulation allows for the development of a narrative that would be difficult to achieve when looking at 50,000 agents or just their summary statistics. Key agent 8 is more highly connected than agent 6 and also provides or has access to twice as much flexibility. The marginal costs of their flexibility is also lower. Agent 6 is associated with aggregator 4 and agent 8 with aggregator 3. Figure 8-25 -Figure 8-26 presents the evolution of Agent_Zero scores for V,S,P and D for two key agents through time for 262 weeks

(~ 5 years)[257].

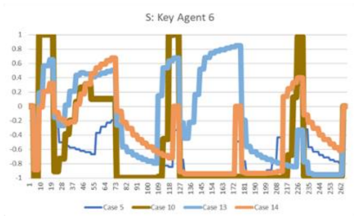


(a) Key agent 8 V Score



(b) Key agent 6 V Score

(c) Key agent 8 S Score



(d) Key agent 6 S Score

(c) Key agent 8 P Score

(d) Key agent 6 P Score

Figure 8-25: Agent_Zero scores for two key agents: 5 year simulation

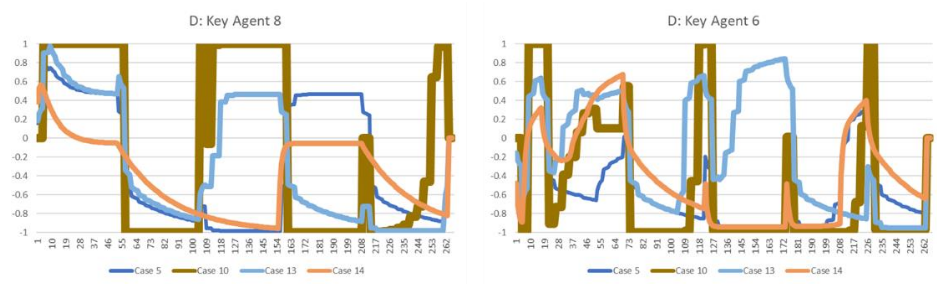


Figure 8-26: Agent_Zero disposition (D) scores for two key agents – 5 year simulation

Key agent 8 get more progressively "angry" with its current aggregator as time

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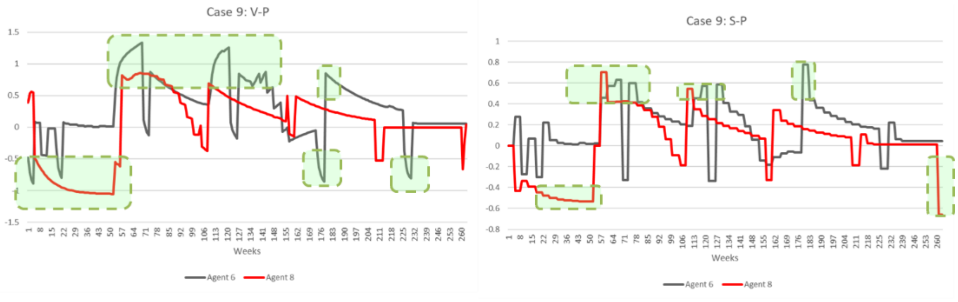
[257] See section 6.4 for a description of agent_zero D, V S and P scores.

goes on (negative V score). Key agent 8 has more connections than key agent 6 does (nearly 400 more), so angry or happy messages are more likely to be propagated from and to this agent. Because it can supply more flexibility at low cost, it would be expected from a revenue point of view, that agent 8 would be much happier than agent 6 would be. That is the case in the early weeks of the simulation but not in later weeks. Figure 8-27 looks at the difference between the V and P, and the S and P, scores for the two agents using case 9.



(a) V-P (b) S-P

Figure 8-27: Difference in V/S and P in two key agents

The differences show how the agent feels emotionally/socially vs its logical position. Large differences[258] mean that the Agent_Zero model will be having more impact than a traditionally logical model. It is clear from Figure 8-27 that there are some periods where there are large enough differences to impact the simulation and results in an impact on aggregator choice at contract end.

On the emotional side agent 6 (higher MC, lower connections and lower volumes) has more V-P events than does agent 8.

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[258] Remember the scale for Agent_Zero has been normalised to 1 and -1.

If one focuses on case 10; it can be seen that on average agent 8 has a higher P score (rational) than agent 6[259]. However, the negative social scores from many connected agents drives down the emotional scores, and affects the dispositional score for the current aggregator. In a similar way to Epstein's "jury" or "slaughter of the innocents" examples [89], social influences flip/override the logical view that an agent may take in this simulation i.e. it may be more logical to select aggregator x, but social influences flip this choice to aggregator y.

8.7 Cost Benefit Analysis of Aggregation

The provision of flexibility/aggregation services, under the right conditions provides net-benefits to customers and other stakeholders. A number of works have quantified these benefits from an infrastructure point of view [10, 11, 13, 567, 599], but none as far as it is known, have quantified the benefits of aggregation from a pure market or price point of view. The simulation here-in provides us with an ability to do this. At its simplest, aggregation reduces average clearing prices over a business as usual case with just generation flexibility. However, this is not the whole story as benefits/costs flow to/from different stakeholders as shown in Figure 8-28. Each stakeholder benefits differently from the other and some can be in conflict.

[259] Higher volumes and lower MC associated with agent 8 would result in higher cleared volumes, and therefore results in higher revenues producing a higher P score.

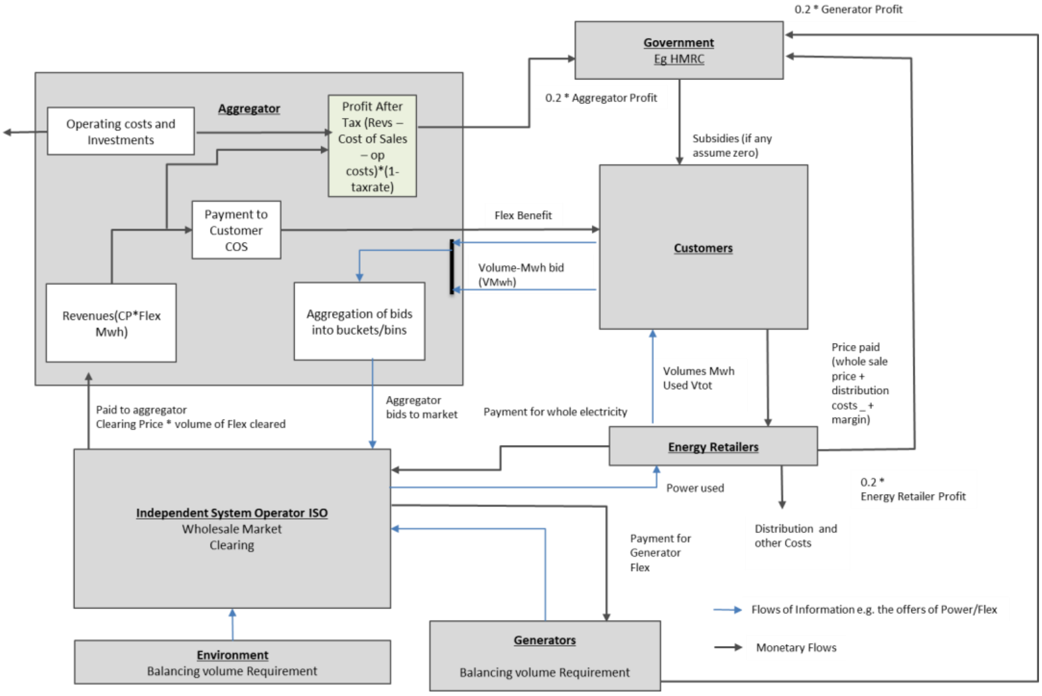

Figure 8-28: Aggregator market cost/benefit flows

Equations used in the assessment of benefits and costs are provided in Appendix L. The equations make the simplifying assumption that "flexibility up" volumes cancel out "flexibility down" volumes over the year so that average volumes over the year remain the same. This is considered a reasonable assumption based on historical data patterns. Using average clearing price values for one year from the various simulations and the equations in Appendix L, stakeholder benefits are shown in Figure 8-29 using different assumptions on imbalance volume levels and the amount of generation flexibility available. Other assumptions are also detailed in Appendix L. The simulation results have been scaled to reflect total UK benefits[260].

[260] That is, multiplied by 20 million/50,000 which equates to Total UK customers/case study numbers.

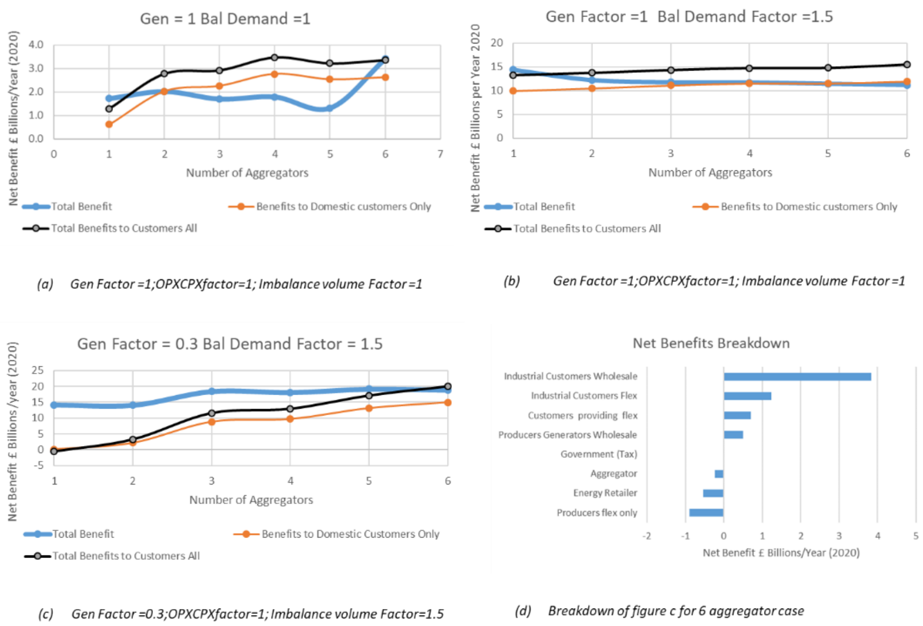

Figure 8-29: Stakeholder benefits

The analysis is based on the data from the first year of a number of simulations and is therefore an approximation. The analysis indicates that 4-6 aggregators will be required to provide positive benefits to the customers in the market analysed. Net UK benefits of the order of £2-20 Billion/year (2020) might be expected from aggregation alone excluding benefits from transmission/distribution infrastructure. This will depend on the state of the market e.g. flexibility available and the level of congestion[261].

8.8 Fuzzy Cognitive Mapping: Making Sense of the Simulations

Fuzzy Cognitive Mapping (FCM) [600-603] is a useful method to help understand the dynamics of complex systems and can be used to aid in the validation of a model.

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[261] Reflected in higher levels of flexibility demand.

It can also be used to involve stakeholders such as regulators in understanding complex relationships and explain their effects in a visual way. Typically, FCM networks would include the significance of the effects of one parameter on another using a strength factor typically between [-1,1]. In the representations below, only the direction of the effect is shown e.g. using +1 or -1. Note future work using NN or multilinear regression representation could be used to derive these values[262].

Software such as FCMapper (Excel) [604] and FCM Expert [605] could be used to create maps and analyse them. FCM expert would be useful in reducing the complexity of such networks in future work.

Figure 8-30 provides a high level FCM for the simulation presented in this chapter. Imbalance volumes, which is effected monthly and yearly through an elasticity effect, is a key driver of clearing price as is the volumes available to provide such flexibility (section 8.2.2).

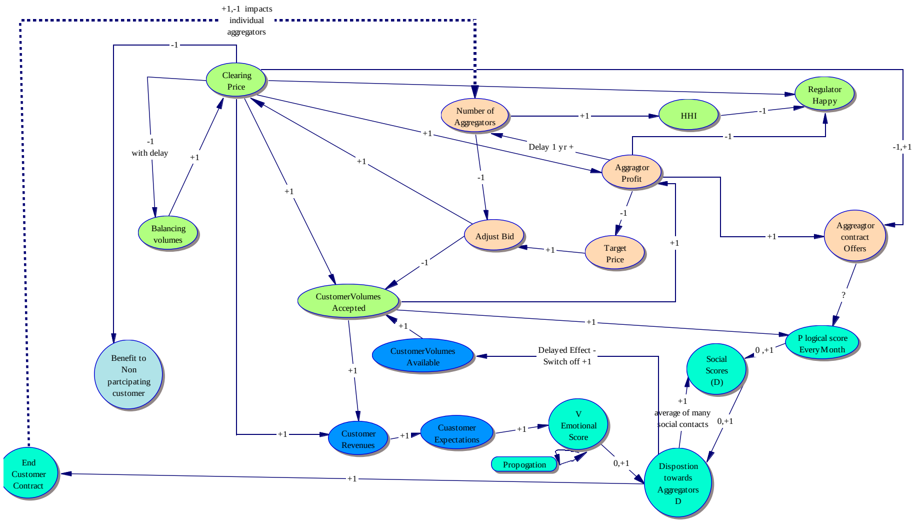

Figure 8-30: FCM of key actors and its effects on clearing price

262 For example, using standardized betas.

Figure 8-31 provides a slightly different map which includes a risk management element shown in purple. Changes in influences are shown with thicker connecting lines

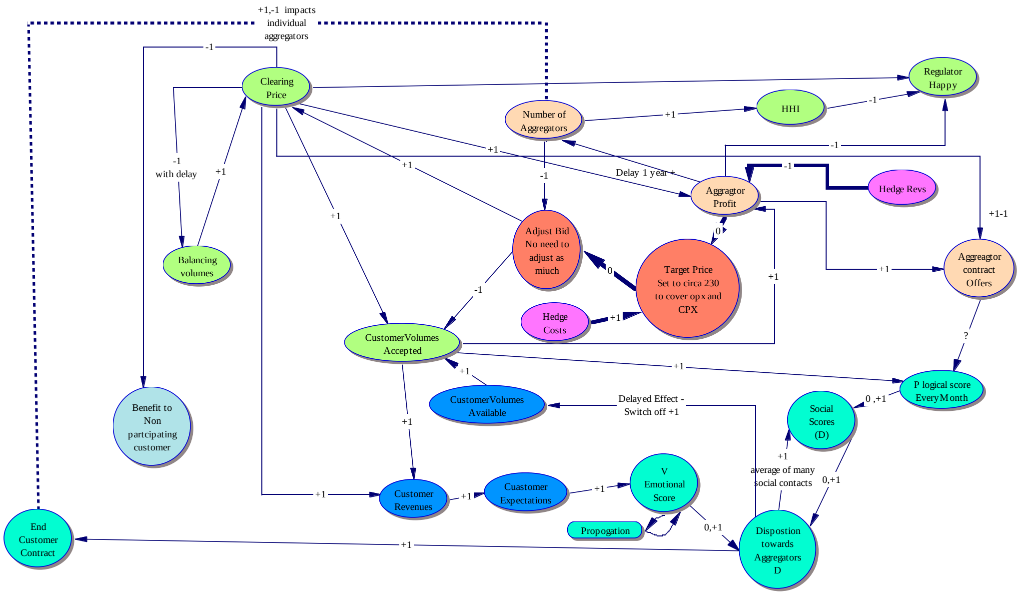

Figure 8-31: FCM with risk hedging effects on simulation

With aggregator risk hedging on, significantly lower clearing prices are seen in the simulations.[263] Clearing price averages appear to hover around a target price that reflects the average cost of covering the operating (OPX) and capital costs (CPX). This is because of the supporting structure of the hedge which dampens the need to adjust target prices to high levels. The hedge "keeps" the aggregators profits on target, without large changes to bidding prices. Although this conclusion could have been reached using "agent tracing", it was found that FCM diagrams proved useful in validating this particular result.

263 That is when comparing runs with risk on and risk off for all aggregators.

8.9 Summary and Discussion

A novel Python based ABM simulation framework for simulating power aggregators and domestic customers in a city the size of Dundee or York in the UK has been constructed. Aggregators can learn to alter bids to maximise profits; domestic customers have been given emotions in the form of a modified Agent_Zero model and can interact with other customers using a social network. "Gossiping" about prices and aggregator performance are currently modelled in a social network. The framework can be extended to include other agent types and it is based on work and coding from the Java based EMLab.

8.9.1 Market Design Implications

There is a natural conflict in the objectives of aggregators, regulators, participating flexibility customers and non-flexibility participants e.g. like those from non-affluent backgrounds or from customers that are indifferent to price and do not wish to be inconvenienced. This is summarized in Table 8-5[264]. Scores indicate the level of acceptance of aggregation under high, middling, and low, clearing price scenarios.

Clearing Price Level	Aggregators	Flex Particpating customers	Non Participants	Government eg HMRC Taxes	Regulators
High	4	4	0	2	-3
Middling	3	2	2	1	1
Low	-1	-1	3	1	3

Table 8-5: Stakeholder views on aggregation and customer flexibility

[264] Authors own view of the scores based on outputs and analysis from the simulations. The table highlights the direction of acceptance and is useful in emphasizing conflicting objectives.

The simulations show that high clearing prices are good for aggregators and under certain conditions (contract types based on margins), good for flexibility participating domestic customers. High prices do not benefit non-flexibility participants[265] and Regulators. Low prices result in reduced and negative profits for aggregators, which may result in market exit and hence reduce market liquidity. This would be a bad outcome for a newly formed aggregator market place.

The output from the linear aggregator model (section 8.2) and Table 8-5 suggest that any market place that can provide a middling clearing price level would satisfy all of the various stakeholders in this marketplace and may result in a successful rollout of flexibility provision in power markets. Of course, all of these results depend on the assumptions/data inputs used within the simulation, so a key area for future research is to obtain more realistic consumer data from surveys, interviews and pilots. This should be combined with consumer econometric and social data like affluence, and technology views. Some of this data may need to be purchased from the likes of Experian using their Mosaic platform [25-27].

8.9.2 Key messages from Simulation Output

- Contract type offers (type, starting prices and margins) at the beginning of market formation will be important determinant of clearing price dynamics.

[265] Non-flexibility participants would typically be associated with less affluent customers those potentially living in fuel poverty.

- Social propagation helps to reduce prices (average effect £30/MWh) and provides an estimated benefit to consumers of up to £0.24 billion per year[266].
- Underlying market structure (need for balancing and the customer flexibility available in any region[267]) has a significant impact on clearing prices, consumer benefits and aggregator profits. A one-size fit all approach to regions with different characteristics could result in a less optimal solution, where no aggregators are willing to participate and the flexibility market ceases to exist.
- It is difficult for aggregators to make profits when generation flexibility is high, in this particular case study. This means that regulators should consider mechanisms to promote the development of the market in these areas.
- Risk management helps to keep clearing prices significantly lower resulting in an overall reduction in average clearing prices of £50/MWh. This could reflect a benefit to consumers of around £0.4 billion per year.
- Aggregator bucketing algorithms will impact clearing prices and aggregator profits significantly.
- The AZ framework can result in behaviours that are in conflict with those that would be taken using logic/economics alone i.e. social influences flip/override the logical view that a rational agent may take in this simulation. However, such behaviour is realistic and usually not accounted for.

[266] Based on 20 million customers at 4,000 kWh/year assuming 10% of CP is reflected in energy retailer prices (20*4000/1000*30)*0.1.
[267] This would be reflected in the power network topology.

- The use of Fuzzy Cognitive Mapping (FCM) in an Agent Based modelling setting, to aid in the validation and understanding of the dynamics of complex systems such as modelled in this thesis, is a new contribution to research.

Chapter 9

Conclusions, Recommendations and Future Research

9.1 Research Objective and Approach

The research objective of this thesis was to deliver an electricity market focused agent based model (ABM) that could allow researchers to experiment with future designs of flexibility markets necessary to enable and achieve a better understanding of the dynamics of these designs. In particular, the focus is on the aggregation of flexibility bids by thousands of domestic customers. Capturing human interactions and corporate behaviours in a social setting was a key aim of the model design. In that regard, a literature review coupled with experimentation on existing ABM systems has been carried out and Java EMLab in Python[268] was chosen as the base framework. Python is easier to use than Java, as it is useful to provide rapid prototypes, and when used with Numpy and Xarray can be extremely fast so the Java based EMLab was ported to Python to create PyEMLab. As far as it is known, it is the first Python power based ABM in existence. Speed issues have necessitated changing the structure slightly to include array vectorised calculations using Numpy, resulting in a speed increase of 10 - 20 times over the standard "list processing" approach taken in many ABM systems. Use of Python scripting allows for the

[268] PyEMLab is a Python port of EMLab (Java), written by the author of this thesis.

simulation of many parameters and the changing of agent roles and learning paradigms. Aggregation will form an important part of any future low carbon network providing flexibility services. EMLab's base agents and structure have been extended to include agents such as generators, domestic and industrial customers, an ISO and aggregators. Customers have been provided with a human behavioural model based on the Agent_Zero framework [89] that combines emotions, cognition (logic) and social influences. It is believed that that this is the first time that the Agent_Zero framework has been used to model customers in the power domain.

Aggregators are represented as corporate entities that optimise profits, adjust bid prices and can risk manage. This necessitated the need to develop a methodology to represent risk and risk management within a corporate setting. Drawing on real examples of risk strategies within energy companies, and by reviewing the literature on options and real options in particular, a novel option based approach has been developed to represent risk in an aggregator. The same approach has been used to represent risk management (hedging) in these agents. The framework can be extended to include more sophisticated risk management strategies including CVaR and Delta hedging with market/exchange options[269]. To simulate corporate aggregator actions, the SmartNet bucketing approach [8, 9, 82] has been expanded and updated. This methodology fits well with the risk management approach developed in the thesis. Existing aggregator simulator models[270] also treat customers and aggregators as marginal cost bidding agents without adaption. Using Cliff's ZIP trader methodology

[269] That is by buying and selling options and future instruments on exchanges such as NYMEX or ICE.

[270] For example SmartNet.

[19-21, 477, 478], agents (customers and aggregators) have been given a simple adaptive bidding behaviour. It is believed that this is the first use of the ZIP trader agent in a power aggregator setting.

Social Network Analysis (SNA) is a very active area of research especially in the social sciences. Social networks have been added to the simulation framework using the Python based NetworkX and SNAP frameworks. These networks, ultimately represented as an adjacency matrix, for speed, have been used to simulate the propagation of "good" and "bad" messages about aggregator performance. Price information is also shared amongst customers using connections on this simulated social network. Different types of social networks including those based on Facebook, Twitter and the small world paradigm [188, 606], have been used to investigate how propagation of these messages changes price dynamics and interaction during the simulation.

Little work has been completed on the effect of social networks on power market dynamics, especially when combined with modelling human emotions. So this work presents a novel view of how customer dynamics can be modelled in a power domain, using a relatively simple but complex framework in the form of an adapted Agent_Zero model [89] on a large social network.

To assess the modelling framework, a case study of an area of the size of Dundee/York with 50,000 domestic customers, 4,500 industrial customers and six aggregators, has been created to prove the use of PyEMLab-Agg in a low carbon context.

9.2 Results and Insights

Many hundreds of simulations have been carried out in testing, validating and experimenting with this simulation model. The effects of various parameters, as well as the impact of modelling paradigms like social network propagation, the effect of agent zero weights, contract starting positions and the effect of risk management have been investigated. The complexity of the model makes it somewhat difficult to understand all of the aspects, so a statistical analysis using techniques borrowed from the social science discipline has been used to analyse these various drivers affecting the model. A derivation of a linear version of this work has allowed the construction of a visualisation of the interaction of these variables. This has proved to be extremely useful in validation and to highlight the various effects that parameters have on the model. Fuzzy cognitive modelling (FCM)[271] has also been used to help understand the complex interactions within the model and in validating such interactions. There is still much work to perform and other agents will be added to the simulation in due course e.g. EV's, P2P providers and so on. The key results seem from these initial simulations are as follows:

- At least four to six aggregators will be required depending on market characteristics (e.g. the amount of flexibility, the balancing demand requirements and so on) to meet regulator/HHI requirements.

[271] Really just a cause and effect map.

- Sophisticated bucketing heuristics like those based on Scargles's Bayesian Blocks algorithm in AstroPy [561, 607] could significantly improve the aggregators performance.
- Aggregator bucketing and bidding algorithms will be an important determinant of future power and flexibility/balancing market prices and dynamics. This will be an area an active area of future research.
- Unsurprisingly, demand for flexibility and the availability of flexibility services are important determinants of price in the market.
- A competitive aggregated flexibility market will reduce prices significantly over the base case of do nothing.
- A one-size fits all approach is not likely to be an appropriate strategy for regulators or companies participating in the market. Under certain conditions aggregators and customers will not perform well and are likely to exit any potential market in the early stages. Careful design should take account of these conditions and look to minimise any potential problems.
- Domestic customers could benefit to the tune of £2-10 billion per year (2023 real terms), from aggregation under the right conditions.
- The benefit associated with lower wholesale prices because of competition in aggregation markets, is far greater (by a factor of 10 - 20) than the benefit associated with directly providing flexibility provision. This is important as those customers in fuel poverty could benefit greatly from the actions of more affluent customers providing flexibility services. Direct benefits of flexibility provision can be relatively small and may result in a lower take up of flexibility

provision. It is therefore important that these customers are nurtured[272] so that significant benefits to all, in the form of lower prices is realised.

- Corporate behaviours such as those exemplified by risk management in this simulation can have a substantial effect on both dynamics and overall clearing price levels. Risk management could reduce average balancing clearing prices by around £50/MWh.
- Encouraging aggregators to offer a diverse set of contracts/services could result in significant price reductions to customers.

9.3 Future Work and Research

There is still much work to perform, but this thesis is the first step to exploring the intricacies of a how a future low carbon network will work using such concepts as aggregation, but by including customer behaviours. Most importantly future work needs to add realistic distribution networks, to the simulation, so that network flows are better represented. This will add another level of complexity to the simulation, but it will be interesting to see how two networks (Power and Social) interact to form different dynamics. Using SNA, these networks could be characterized[273], to see if there are any links between dynamic patterns seen in the market and the types of networks used in the simulation. The results in section 8.4 indicate that system dynamics do

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[272] For example, highlight the benefits of lower prices as well as the direct benefits seen from flexibility provision.

[273] Different networks structures can be represented by network statistics such as average characteristic path length, degree, clustering density and so on.

differ when social network interaction patterns are changed.

Detailed power distribution network data on large networks is not readily available in the public domain. However, DING0 [608, 609] was developed precisely to overcome this issue and it may prove useful in providing many synthetic distribution networks for researchers. Unfortunately, this addition is likely to increase runtime significantly so in the longer term a simple representation of congestion issues and its effect on flexibility may be useful. Ideas for representing the networks as Neural networks like those in references [610, 611], may also be useful.

9.3.1 Economic dispatch Vs OPF

To simplify power flow calculations and make computation run times reasonable, an economic dispatch (ED) formulation of the market has been used to clear the market. Economic dispatch assumes market clearing without any power flow calculations. It is a fast methodology, omitting network details and assumes no losses[274].

Optimized Power Flow (OPF) [612, 613] can be used to account for network representations[275] and costs and used to derive the clearing price in these zones as well as individual distribution nodes. OPF can be used at the distribution level to calculate power flows, identify congestion issues and provide locational marginal pricing at each node. Such an approach would provide clear signals to flexibility providers. Software formulations such as MATPOWER [176, 177], PyPower [187] and PandaPower [614]

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[274] Losses can be accounted for by assuming that supply will need to be higher than demand by an average loss factor.

[275] Losses are calculated as part of OPF.

can be used to specify and solve AC OPF problems, but calculations can be time consuming for large systems. Future work will include an OPF model and in that regard tests have been carried out using the PowerGama [28, 29] and PandaPower frameworks.

9.3.2 Incorporating EV's into Future Work

Electric Vehicle's (EV's) are currently represented in the simulation as a single static entity. Ideally, a future model would include mobile units (agents representing EV movement) and allow modelling of charging and discharging across the network in response to price changes. There are currently no EV ABM models based in Python that we know of and few that take account of pricing. A Python prototype that simulates drivers in Netherlands using data and modelling methodology from work outlined in [581] has been constructed, although the model has not yet been linked to PyEMLab. Although it would be a relatively simple task to do so[276]. Daina et al [582] have developed a methodology that incorporates charging price as one of its variables and uses stated response surveys to create a linear based algorithm/heuristic that is used to choose from a variety of discrete options e.g. charge, no charge or stay at home. It would be useful to incorporate this methodology in the EV ABM model discussed above as it models price impacts in a more simplistic way. Note none of the ABM EV models that have been investigated incorporates V2G interactions i.e. selling battery storage back to the grid. Storage decisions via a storage aggregator has been modelled in the SmartNet project [6] and could be incorporated later.

[276] The downside would be increased run times.

9.3.3 A More Sophisticated Emotional Model: Emotions Affecting Cognition

Agent_Zero has proved to be a useful framework for representing a "simple" emotional and social response in the simulation, but the current framework ignores links between emotions and cognition[277]. In the context of this simulation, it would be rational to assume that angry customers would treat aggregator contract offers differently from those that were happy. This may have a dynamic impact on the AZ module weights, or it may change parameters in the logistic equation used to provide a logical contract utility value. The appropriate design and use of customer survey data/interviews might allow us to better model these effects and chose an appropriate modelling environment for further AZ extensions. Without this survey data, it is not clear how emotion/cognitive issues would affect customer interactions with the market and is therefore a future key research objective.

9.3.4 Different Flexibility Service Provisions

The current framework focuses on aggregation but other business models as discussed in Chapter 4 would be available to stakeholders. The PyEMLab-Agg framework allows for the easy introduction of these additional business models and any additional agent types. Abstract versions of some of these agents have already been added to the model e.g. P2P.

Different customers will be drawn psychologically to certain services rather than

[277] Note the current simulations have an indirect link in that when the AZ dispositional score D < -0.2, domestic customers stop bidding. Social influence and extinction in the AZ framework can increase this value over time.

another e.g. some will prefer P2P to aggregation; some will just prefer to stay with their current retail energy retailer. The current Agent_Zero emotional model will need to be adapted to model these competing services both from a logical and emotional point of view. Connectionist models[278] like those discussed in Chapter 6 could provide a methodology to represent the competing emotions between these different services. Alternatively, the Rescola Wagner model could be modified.

9.3.5 Other Future Work

Other work that future researchers could consider are as follows:

- The inclusion of CO2 and commodity markets and investment in new generation (as modelled in the EMLab/ base PyEMLab).
- Extend model to include customer reactive power services.
- Extend AZ to Industrial customers and possibly aggregators.
- Investigate the effect on the simulation of customer mix e.g. the effect of customer affluence on network (social and power) and simulation dynamics.
- The addition of other learning paradigms such as reinforcement learning and learning automata.
- The addition of a more realistic risk management strategy that uses exchange instruments like futures and options.
- Research into the use of more sophisticated portfolio management techniques for bucketing; e.g. to include risk management and other clustering parameters into bucketing algorithms or the use of genetic algorithms.

[278] Those that represent memory and cognitive performance, typically using neural nets, genetic algorithms and deep learning.

- Investigate aggregator “cherry picking” behaviour effects on market evolution and customer benefits.
- Modelling of more sophisticated aggregated business models the inclusion of sophisticated geographically and digitally based aggregators e.g. Google, Amazon.
- Include models of congestion within aggregator agents.
- Updating social network interactions to include inputs from aggregator companies, from regulators and from media outlets like newspapers. For example, newspapers report on retailer price behaviour and such news spreads more widely and more quickly than the normal routes via consumer’s social connections, resulting in an avalanche of contract switching actions.
- The addition of a Regulator agent to the simulation.
- Extend the framework to include human or hardware in the loop [615-621].
- Norm and coalition modelling.
- Further validation of the model especially once data is obtained from work on consumer surveys on attitudes.
- The addition of other elements discussed in the ideal simulator discussion (section 3.3).

There is much work to do here but it is hoped that this framework will help researchers to simulate the evolving issues and challenges in this important fast changing area. It provides a relatively easy to use framework, to which additional agent types can be added. Python scripting allows for easy modification of parameters and agent roles. Social network representations and the use of a modified Agent_Zero framework has allowed the representation of human behaviour in a social setting in a relatively “simple” but sophisticated way. The investigation of the effect of message propagation and emotions on the dynamics of aggregation in a future low carbon network setting shows that these emotional and network effects are significant and supports the idea that it is important to model psychological/behavioural effects in power markets.

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Appendices

Appendix A: Analogous Industries: Lessons for Aggregators

Other Industries provide useful lessons for future aggregators in the context of business model evolution and in the evolution of competition in newly forming markets. US gas retailing companies in the 1990's and 2000's developed sophisticated gas business models that included storage businesses that used trading and risk management principles that are rarely used in European businesses. The mid 1980's and early 1990's provide some useful clues as to the evolution of embryonic or newly formed markets which may prove useful to companies entering the aggregation business market. An analysis of this data shows how margins have reduced rapidly over a few years as competition opened up. Companies also sustained losses for a number of years before exiting the market and consolidation of companies is likely to occur in the longer term.

A.1 Industrial Gas Markets in the United States

A.1.1 Background

In the United States, gas marketing as an industry evolved out of the development of open-access transportation of gas in the mid-1980's. Marketing companies sold gas, often re-bundled with interruptible transportation, at unregulated prices that were lower than the prices paid by pipeline company customers for regulated sales service.

A.1.1.1 Competition

However, increased competition following re-structuring led to an environment where firms evolved to offer many different types of services to remain competitive. Creating different value-added combinations of supply and transportation services resulted in increased revenues and profits for marketers. A wider array of services was being offered[279], including supply aggregation, supply procurement, balancing, capacity reservation, storage facilities and risk management services. These services have been offered since the mid 1990's in the US gas market.

The result has been that many marketers/retailers have consolidated to remain competitive, whilst many smaller firms went out of business. The further evolution of this segment of the industry depended on issues such as the ability to capitalize on new business opportunities, market hubs, storage access and to maintain creditworthiness.

As margins on reselling gas in the US became thinner because of competition, the use and creation of financial tools enabled marketers to differentiate their services, gain more market share, boost their revenues and increase profits. However, using risk management techniques can result in substantial losses as well as gains.

A.1.2 Consolidation and Diversification

Growing competition in the US led to the development through time of fewer, larger firms. These mergers and acquisitions have taken place for the following reasons:

- To diversify the mix of services offered as margins fell. Rather than expanding internally, marketers purchased or teamed up with other firms.

[279] And is still is – in deregulated markets.

- Security of supply. Alliances with producers became more common as marketers sought more secure supplies of gas, and producers sought greater marketing expertise.

- Merging allowed marketers to reach more customers. Wider geographical markets enabled marketers to increase market share.

- To strengthen their financial position. By merging with larger firms, smaller companies were able to eliminate concerns about their credit risk.

Historically, creditworthiness has been the downfall of several US marketers[280], as they have been unable to meet stringent credit requirements. In the US, creditworthiness is the lifeblood of gas and power marketers, as they frequently act as the intermediary between buyers and sellers of gas and need credit to serve as collateral in case either of the parties to the transaction defaults. Marketers who are not considered creditworthy by a producer will not receive supplies. Credit is less of an issue for those marketers owned by major producers (large oil companies), banks or pipeline companies and therefore backed by asset-rich balance sheets. This provides their marketing subsidiaries with equity support to expand volume of throughput by using varied financing tools and the power of their parent company.

A.1.2.1 US Gas Prices

Figure A-1 shows historical US industrial, spot and wellhead gas prices - over 10 years during the early formation of the market. It is clear that there is a correlation

[280] Both in the gas and power markets.

between delivered industrial prices and the wellhead/spot price281 but industrial prices fell more sharply. Prices fell as competition in the market took hold.

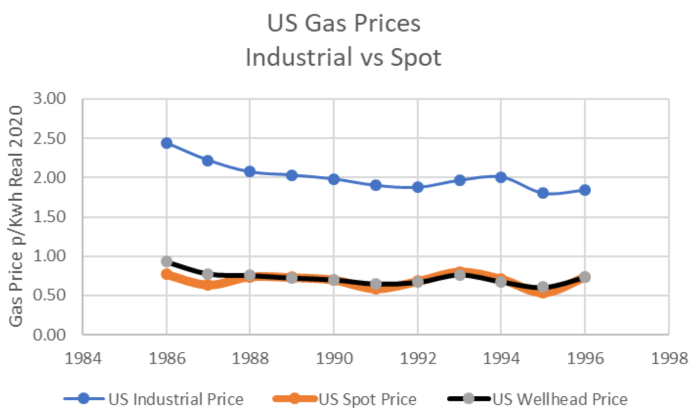

Figure A-1: US natural gas prices 1986-1996

A.1.2.2 US Gas Marketer Margins

The differential between industrial (factory gate) and spot/wellhead prices is made up of transportation, other costs/overheads and the marketer's margin.[282] From previous analysis on transportation and operating costs, an estimate of operating margins of marketers in the US, has been made.

Figure A-2 shows these US marketer margins over the period 1986-1996. The margins are plotted for marketer supplies from both spot and producer sources, and reflect the decline in margins as penetration of the market by marketers has increased. Margins in the mid 1990's, would appear to be in the range 2 - 8%.

[281] The cost of producing the gas.

[282] Retailers typically bought this gas off the spot market or from offshore producers and sold this on at industrial prices. The difference between these values after other costs such as transmission and distribution/Admin represents the retailer's margin.

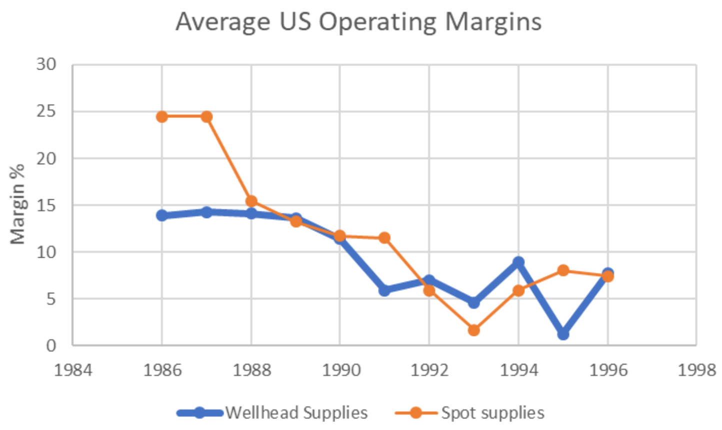

Figure A-2: US natural gas: Average US marketer operating margins

In the next section, the UK industrial gas market is analyzed, to highlight any parallels that can be drawn with the US experience. Although the UK deregulation process started much later than in the US, there are some similarities. The time-period analyzed for the UK is also much shorter, from 1993 to 1996.

A.2 Industrial Gas Markets in the United Kingdom

A.2.1 The UK Industrial Gas Market in the early 1990's

Gas is used across the industrial spectrum in the UK and examples are; Iron and Steel, Engineering, Food, Drink & Tobacco, Paper & Printing, Minerals & Mining and is also used for power generation

Industrial gas demand is driven primarily by the level of economic activity in the UK, and is split between tariff customers (~6% of volume in 1996) and contract supplies (~94% of volume in 1996). The contract market was further divided between firm customers (~36% of volume) with guaranteed supplies, and interruptible customers (~58% of volume) who may have their supplies cut off for varying periods at the supplies discretion. The interruptible customers are responsible for ensuring that they have an alternative fuel source available. The gas price paid varies considerably according to the type of supply (firm or interruptible). However to simplify the analysis the graphs that follow show an average "firm" price across all sizes and type of customer.

A.2.1.1 UK Gas Prices

Figure A-3 compares UK firm industrial and spot gas prices since the beginning of 1994. Firm industrial prices reflect the average gas price paid by all sizes of firm industrial customers. Prices in the firm market have shown a steady decline from highs of over 1.5p/kWh (real terms 2020) in early 1994 to levels of close to 0.8p/kWh in 1996. This decline has been led by the spot price, which over the same time period, has fallen from 1.3p/kWh to 0.78p/kWh. Note that margins have fallen rapidly.[283]

It appears from this figure that the industrial price is related to the spot price albeit with a time lag. Thus the industrial/spot prices link in the US also appears to occur in the UK.

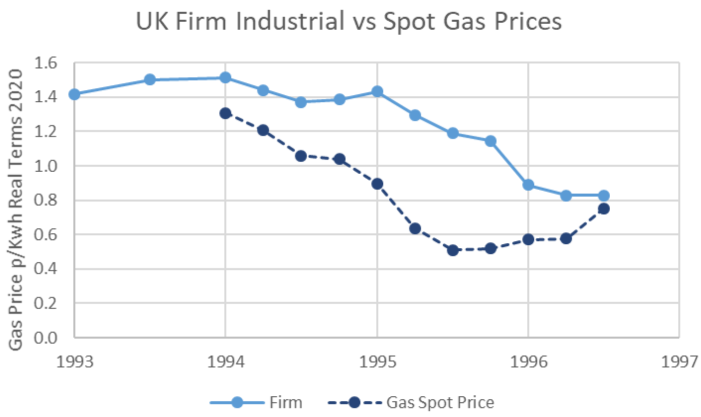

Figure A-3: UK gas prices 1993-1996

A.2.1.2 UK Market Share vs Margins

Using published financial data from a number of energy retailing companies over the period 1993 – 1995, operating margins (i.e. revenue-costs before taxes), have been extracted and plotted against turnover, which has been used as a proxy for market share. Figures A-4 to A7 plot operating margin and turnover for the years 1993 to 1995.

[283] Difference between industrial and spot price is nearly zero.

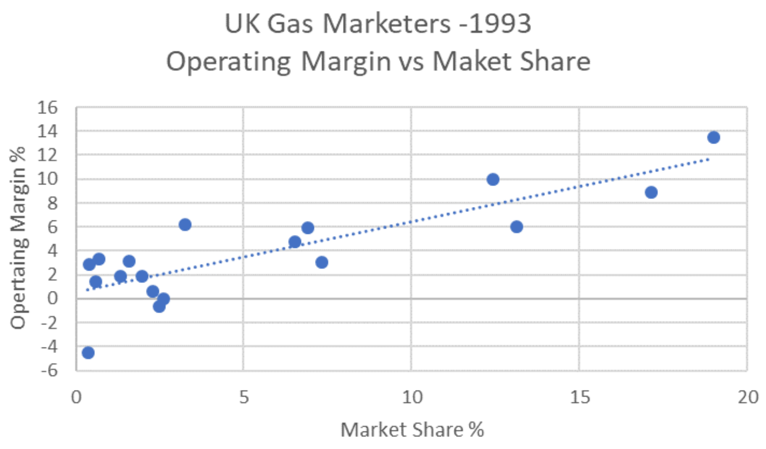

Figure A-4: UK gas retailer operating margins 1993

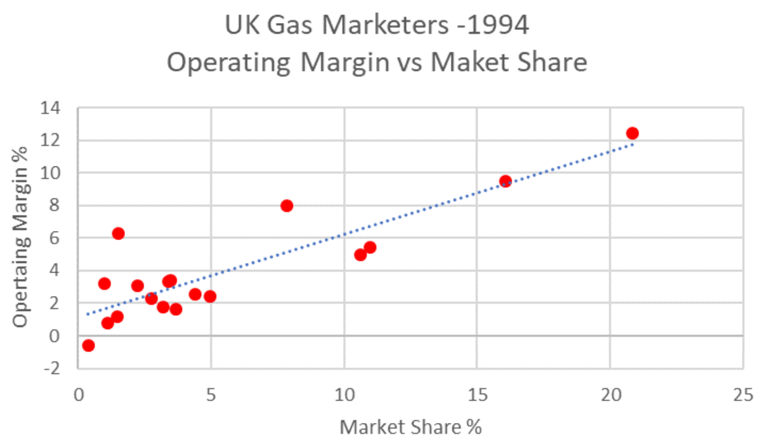

Figure A-5: UK gas retailer operating margins 1994

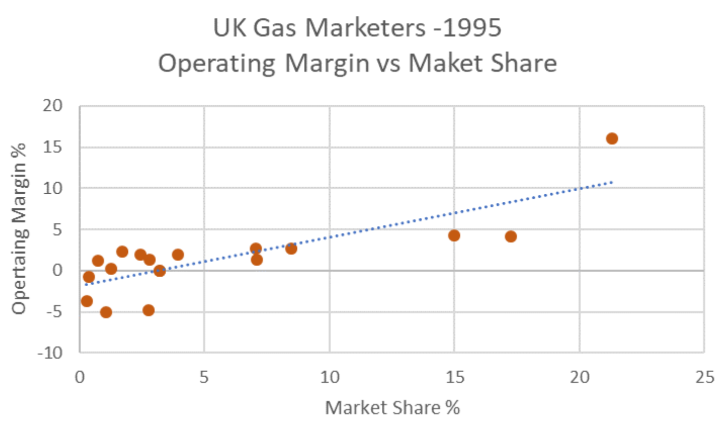

Figure A-6: UK gas retailer operating margins 1995

Note that these graphs appear to show that:

- The operating margin increases with market share, as expected.
- The negative slope of the trend line flattens through time i.e. margins are reducing as competition bites and the market evolves.
- For those players with a 15% market share, margins have probably reduced from 9% to 7% over two years.
- Margins for smaller market shares are low and can be negative.

A.3 Analogous markets (Airlines and Retail)

In the following section a discussion about the margin experiences seen in other industries is given, highlighting those lessons which are applicable to the future power aggregation industry in the UK. Similar but slightly different trends are seen in all of these industries but it is clear that companies will and have made losses for many years in some of these markets. It therefore may take some time before aggregators making losses exit the market.

A.3.1 US Deregulation : General Trends

The experience of US companies after deregulation provides a valuable road map on what might happen in a newly formed aggregator market. The analysis below highlights the pattern of competitive dynamics that unfolds when artificial constraints are suddenly lifted and new entrants allowed to rush in.

In the US telecoms market, prices of long distance telephone calls (previously companies' most profitable business) fell 38% in the 4 years after deregulation.

However, prices on local services rose by around 43%. In the US airline industry, many prices fell by around 42% while prices on previously less profitable routes rose. In short, what appears to have been a less attractive market before regulation often becomes more sensible post-deregulation as the more savvy competitors avoid the rush of new entrants and anticipate large price changes (both up and down). Thus, the variation in profitability widens [205].

Each deregulated industry saw profitability deteriorating quickly as new entrants shattered pricing for all competitors for at least 5 years. The surprise to many was that it took only one competitor with small market share to shatter prices for everyone. Price reductions of 30-40 % ensued but resulted in surprisingly little gain in overall market share.

After five years of intense competition in the US airline industry, the strain on industry performance forced many of new entrants to leave (66%) and within 10 years some 56% of the larger players had also left.

It was found that successful low cost entrants do not compete on price for very long. They generally specialize. Typically, there are no more than 5 - 7 firms that remained as broad based competitors after 5 years of deregulation.

A.3.2 Competitive Margins

The 'PIMS' study in 1974-1975 [206, 622] showed that pre-tax returns on investment [ROI] (i.e. pre-tax profit/investment) were related to market share and that they typically ranged from around 10 to 30% as shown in Figure A-7.

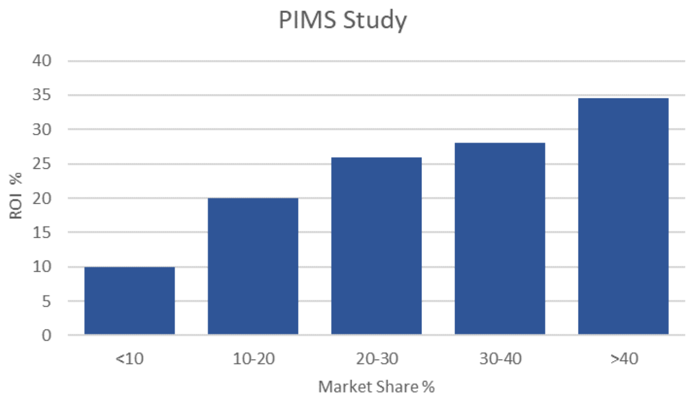

Figure A-7 PIMS study results

The study also highlighted relationships between ROI and other variables such as R&D spend and company types. ROI is related to pretax profit margin by the inverse of the turnover efficiency ratio (i.e. Turnover/Investment). A typical value for this in the electricity retailing business is of the order of 10. This means that the ROI presented above would equate to profit margins of 1 to 3%. In the case of an integrated oil company like BP (they may enter the aggregation business) these 'PIMS' values would equate to 5 - 12%[284]. However, there is a different level of risk associated with this business and of course a different degree of competition.

A.3.3 Electricity Supply Business Margins –1990's

Although all electricity supply companies give details of their overall corporate profitability in their annual reports it appears that only Eastern Electricity[285] broke down their accounts by business type during the 1990's. Their 1994 annual report

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[284] They have different turnover ratios.

[285] Eastern Electricity was one of the 12 regional electricity companies offered by the Government for privatisation in 1990. It covered the areas of Cambridgeshire, Hertfordshire, Huntingdonshire, the Isle of Ely, Norfolk, Suffolk and parts of Bedfordshire, Buckinghamshire, Essex, Middlesex, Oxfordshire and the Soke of Peterborough. Eventually the distribution rights of Eastern were sold to EDF energy.

indicates that the profit margin on their retailing business was some 1.1%. Note current margins in recent years have been much higher (~ 5%) [623].

A.3.4 US Gas Marketers

Section A.1.2.2, outlined the results of analysis into the US gas market, where it was estimated that the margins being earned by marketers after the market was liberalized was is in the range of 2-8%. This range reflects both the maturity of the market at that time, and the extent to which marketers have diversified the services they offer. That is they are no longer just selling electricity or gas but provide other services or sell across geographies.

A.3.5 UK Energy Marketers

Analysis of publicly available data in 2000 (summarized in Section 2.2 below) indicates that margins for the smaller energy retail companies at that time, seem to be around 2-3%.[286] These companies are buying and selling both gas and electricity products. In its simplest terms these gas marketer were taking little or no risk. There is therefore little premium that a 'non risk taking' gas retailer should earn in a fully liquid and competitive market. On the other hand, a wholesaler who has either developed an offshore gas field or large power generation or buys gas/electricity on a long-term basis is taking a much larger risk. In the domestic market, the profit margin historically paid to British Gas (BG)[287] has been of the order of 0.27p/kWh (real terms 2020 over the period 1971 -1991). This equates to a profit margin of around 30%[288].

286 Analysis of public accounts.

287 Originally a monopoly buyer of gas pre 1990.

288 Author's calculation.

Over time, this this profit dropped to 0.03-0.1p/kWh[289]. This equates to 7-14% profit margin. British Gas (now Centrica) is an example of a company that would be called a wholesaler or an aggregator.

A.3.6 Margins over time/Domestic Margins

The analysis above shows that profit margins in the UK industrial market are linked to market share, and have reduced over time. The analysis above appears to show that average margins in the Industrial gas market have reduced from above 10% in 1990/1991 to between 1 and 2% by 1995 (Figure A-8).

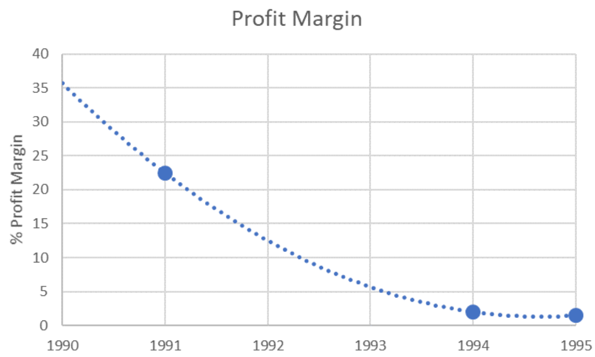


Figure A-8: Profit margin evolution

This curve follows an exponential decline and fits well with a view that margins decline by an exponential diffusion process. Similar patterns were seen in the US gas retailing market but declines took longer. One might expect that aggregator margins will decline with the same characteristics. In industries like US airlines and telecommunications markets margins were eroded within 1 to 2 years.

[289] Authors calculation.

A.3.7 The US Airline Industry

Until 1978, the US airline industry was regulated, thereafter migrating to a profit based industry which moved from conventional selling to low cost distribution. The US airlines contributed through various moves and counter-moves to large-scale destruction of value. In summary, the evolution of the airline industry in the US was as follows:

- Airlines initially spent money to differentiate their service from their competitors.
- Post deregulation in 1978, the airline business became a commodity market.
- Players fought aggressively to expand market share.
- The consequent reduction in prices expanded demand for service from leisure travelers.
- Some players expanded too quickly, lost money and left the industry allowing profitability to improve. However, this situation did not prevail for long.
- In efforts to win market-share, airlines invested in new airplanes that were not needed. These additional aircraft caused further reductions in utilization levels causing further reduction in price.
- Airplanes were not retired when players left the market leaving utilization at around 50%. Thus high fixed cost assets with low utilization led to price wars.
- The result was that after five years of deregulation some airlines merged with their rivals and others withdrew from the market.

- The economics of this business was such that it made sense for companies to reduce prices rather than lose market share.

A.3.7.1 Lessons Learnt

Operating margins fell from 6.1 % in 1978 to -2.5% in 1990, but recovered in the 1990's. The losses suffered in the early 1990's are partly the result of the Gulf War in 1990-91, when few Americans travelled abroad and partly due to recessionary impact upon business and leisure travel.

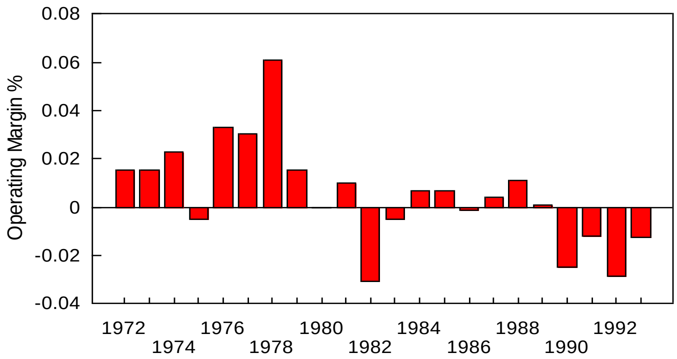


Figure A-9: Airline industry profitability 1970 -1993

However, the data appears to show that the US airline industry follows a business cycle of anything from three to five years, and that profitability in the industry remains fickle.

A.3.7.2 Differences between US airlines and UK Energy Industry

Although it would appear that the US airline industry has been on average a zero profit making industry over the last 20 years there are some important differences to consider when comparing their experiences with the UK energy market. These are:

- There is a utilization of 50% in US airlines, but even though companies went bankrupt airplanes were not retired as banks were willing to sell them off to new entrants to get some payback for their debts. New players therefore started off from a lower cost base than existing incumbents.

- Many of the larger UK aggregator players are unlikely to go bankrupt as most are likely to be subsidiaries of larger organizations. In the UK gas industry a smaller number of players, control the industrial gas market. In the 1990/2000's the top six players control over 75% of sales to the industrial gas market.

Appendix B: Return on Equity; Additional Graphs

This appendix provides a set of additional graphs that show the variation in breakeven clearing prices and returns on equity with changes in parameters like Beta (Risk), the number of domestic customers and so on. This is in addition to the work presented in Chapter 4.

B.1 Max Bid to meet ROE Targets

Max value that can be accepted as a bid if the aggregator is to meet its return on equity targets consistent with Beta values shown.

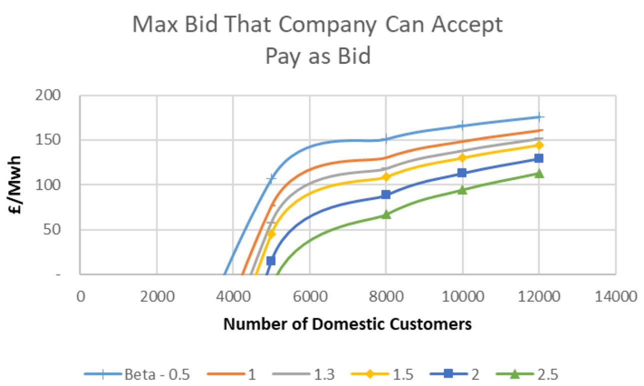


Figure B-1: Max bid to meet ROE targets by domestic customer numbers

B.2 Profit Margin Variations with Clearing Price

Profit margin outturn (%) with number of domestic customers where the bid price is set to a % of the expected clearing price. All graphs for the pay as bid model. That is, the aggregator pays customer their bid price.

Clear price = £300/MWh

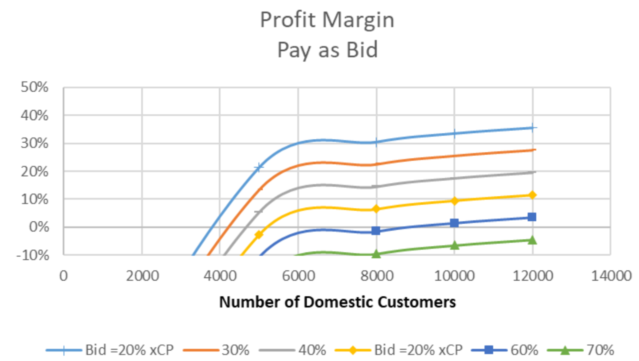


Figure B-2: Aggregator profit margin variation; Clear price = £300/MWh

Clear price = £200/MWh

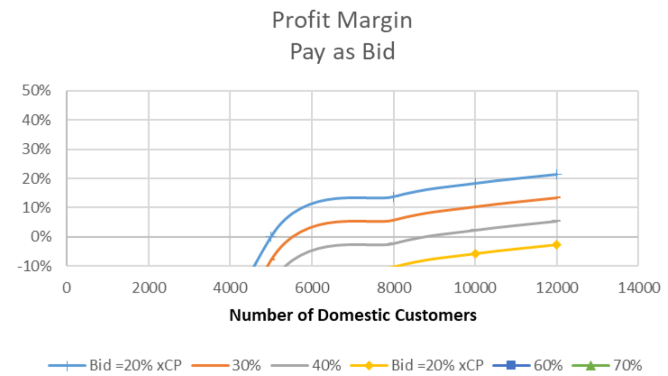


Figure B-3: Aggregator profit margin variation; Clear price = £300/MWh

B.3 Aggregator Margin Requirements vs Contract Type, Beta …

Minimum Aggregator profit margin requirements for the pay a % of the Cleared price case vs number of customers.

Pay % of clear price to customer is shown

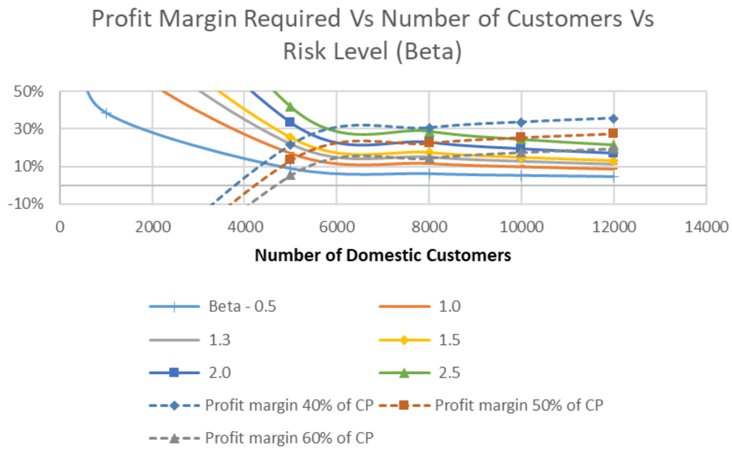


Figure B-4: Aggregator profit margin requirement

Solid lines represent the minimum profit margin required for different risk i.e. Beta. Beta determines the expected ROE for that company and hence profit margin. The dash lines represents the profit margin achieved for different margins to the aggregator in the Pay % of clear model. To be profitable the aggregator must chose a business model (dotted line) with an appropriate level of customers that is above the expected level of profit margin at the business risk level (beta) i.e. the solid lines.

B.4 Aggregator Profit Margin Variation

Accounting profit margin for the pay a % of the Cleared price vs number of customers. Note Margin is the margin to the aggregator.

<u>Clear price = £300/MWh</u>

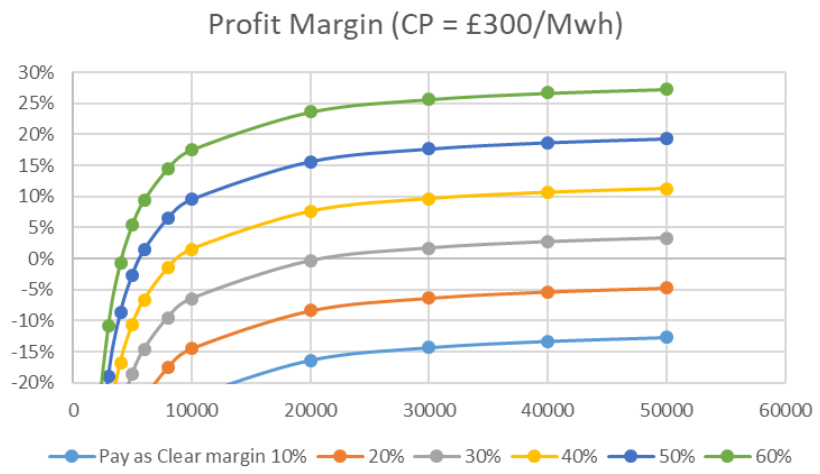


Figure B-5: Aggregator profit margin; Clear price =£300/MWh

<u>Clear price = £200/MWh</u>

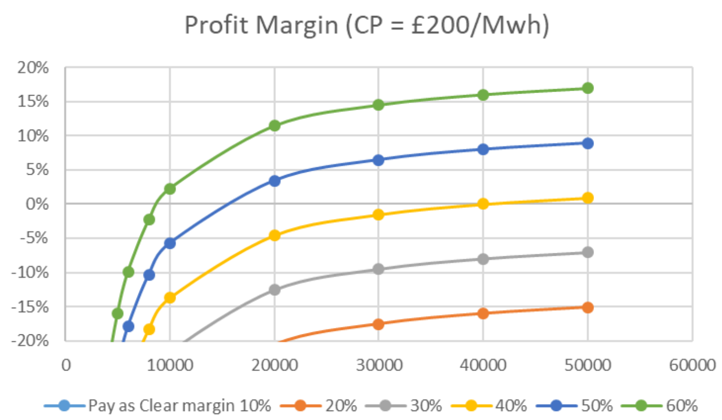


Figure B-6: Aggregator profit margin; Clear price =£200/MWh

B.5 Minimum Aggregator Margin Requirement

Note "Margin" is the margin to the aggregator. With the following assumptions what will be the minimum margin that the aggregator should take to meet its ROE/Profit margin targets.

<u>Clear price = £300/MWh</u>

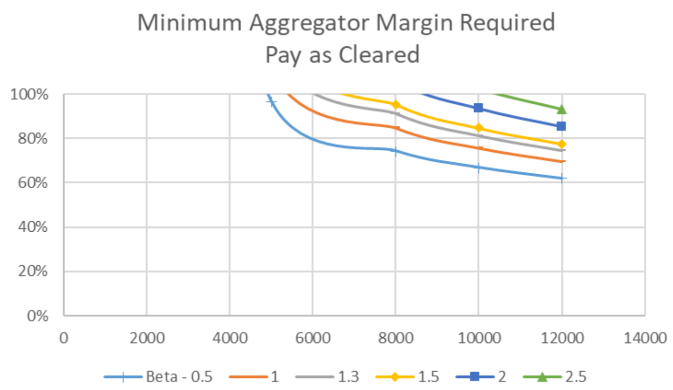


Figure B-7: Minimum margin required to breakeven; Pay as cleared CP =£300/MWh

<u>Clear price = £200/MWh</u>

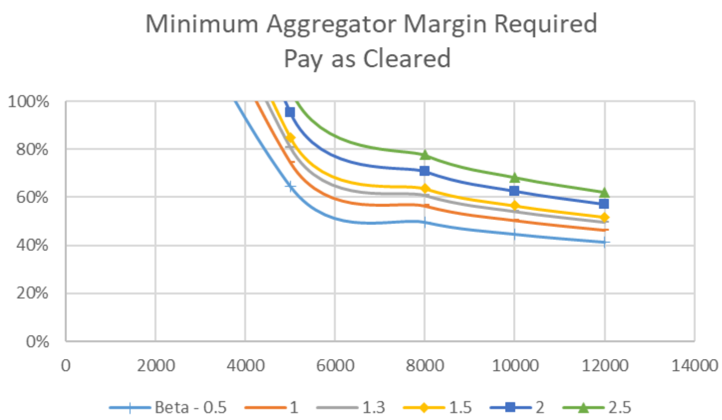


Figure B-8: Minimum margin required to breakeven; Pay as cleared CP =£200/MWh

Clear price = £500/MWh

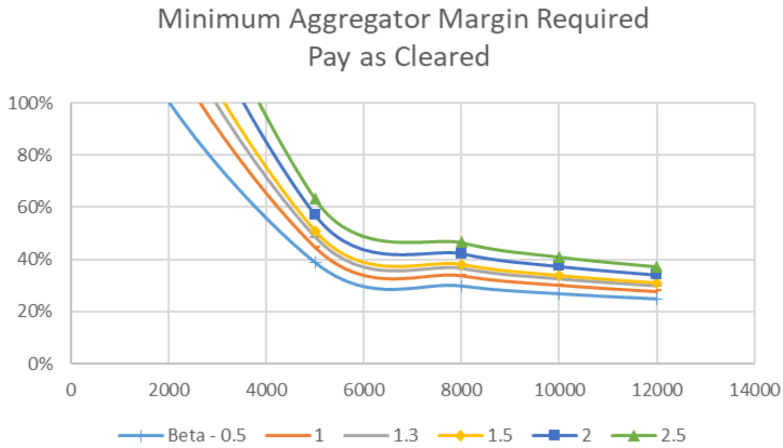


Figure B-9: Minimum margin required to breakeven; Pay as cleared CP =£500/MWh

Note it is currently believed that aggregators in the market are only receiving 30% of the cleared price. Based on the assumptions of the costs supplied, it would appear that this model would only be sustainable with clearing prices in the region of £500/MWh on average and with 6000-10000 customers. Note the base assumption is that 50% of the max potential of the flexibility is available. If this were to rise to 75% then a price of £350 - 400/MWh would be required. With half of the operating costs and a 50% take up this clearing price requirement would drop to £300 -£400/MWh.

B.6 Variability in Profit Margins with Amount of Flexibility

Note that to make a 10% profit margin that flexibility volumes needs to be relatively high i.e. > 50%.

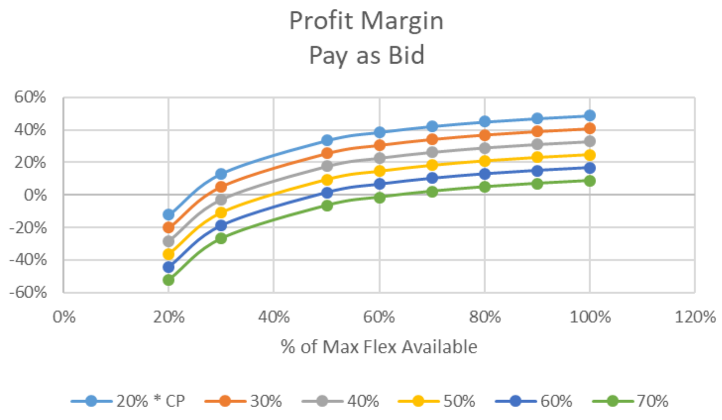


Figure B-10: Profit margin; pay as bid vs max flexibility

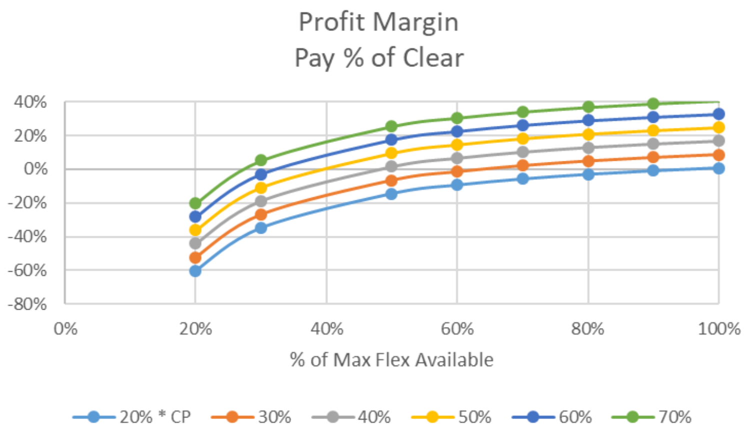


Figure B-11: Profit margin; pay percentage of clear vs max flexibility

Appendix C: Options; General Overview

C.1 Option Theory - Financial

The famous Black Scholes formula [270][290] for valuing options, uses the movement in an asset's price essentially stock or share price or a commodity price to value the likelihood of that price being above some value the exercise price. The Black Scholes option valuation depends upon the following factors:

1. The current spot price of the underlying asset S (or assets in our case; three of them)
2. The exercise price or strike price at which the option has been struck (X or K)
3. The price volatility σ of the underlying asset (or asset)
4. The risk free interest rate (r) or discount rate
5. The time to expiry t – which is relatively small in the case of options in this thesis *e.g.* 1 hour or maybe 10 days if we use a hedging strategy using futures
6. The dividend yield on dividend paying securities- not applicable in this case
7. Whether it's a put or a call

For a call option higher volatilities result in higher option prices – unless the option is so far out of the money it does not affect it. That is the price of the asset is either

[290] Wilmott's book provides a good introduction to options and Black Scholes formula [270]. Note the original Black Scholes paper can be found here - https://www.cs.princeton.edu/courses/archive/fall09/cos323/papers/black_scholes73.pdf.

$>>>$ or $<<<$ exercise price of the option.

Longer periods to expiration, increase the value of the option but in our case, periods are small (1 hour). Note our volatilities during these small-time frames are high. UK balancing price volatilities in 2015-2020 period were of the order of 20 % (hourly). Higher asset or commodity prices result in higher option values assuming the asset price is above or near the exercise price. Higher exercise price (in our case the minimum price we need to cover our costs), the lower the value of the option. Even though the options in this thesis are valued differently from the standard vanilla Black Scholes model the general conclusions of price and volatility movements still hold. Put options drive the value in the same way but the movement of option value to commodity price and exercise price will be the reverse of that discussed above.

Appendix D: Pseudo Code for Three Asset Aggregation Risk Option

This code is based on an algorithm presented by Haug [309] for a three-asset Monte-Carlo option (with correlation) and adapted for an aggregator risk evaluation as discussed and presented in this thesis (Chapter 5). Details on the Box Muller and Halton algorithm are provided in [309] . This is a general algorithm and calculates both call and put option values. Final values are calculated for the three different revenue models discussed in Chapter 4/5 of this thesis. Namely:

- AssetValue_payasbid
- AssetValue_pay%ClearPrice
- AssetValue_payfixedprice

```
#Inputs => CallPutFlag, S1, S2, S3,X, T, r , v1, v2, v3 ,rho12, rho13, rho23,  nSimulations,
margin, Pfixed
# S1, S2, S3 expected asset value
# S1- Clear Price
#S2 – Volume of Bid MWh;
#S3 – Bid Price £/MWh
# X – exercise price – that is the min profit required by the aggregator ; r – discount rate; T –
    time to expiry (years)
# V1 V2, V3 - Volatilities of assets S1,S2,S3 … (yearly volatilities)
# Correlation coefficients - rho12, rho13, rho23
#margin – margin % of revenues  paid to aggregator ; (1- margin) to customer
#Pfixed  - Fixed price £/MWh paid to customer
   If CallPutFlag = "p" Then Z=1 else Z=-1              # p = put; c = Call
   Drift1 = (b1 - v1 * v1 / 2) * T
   Drift2 = (b2 - v2 * v2 / 2) * T
   Drift3 = (b2 - v3 * v3 / 2) * T
   v1Sqrdt = v1 * (T)^0.5
   v2Sqrdt = v2 * (T) ^0.5
   v3Sqrdt = v3 * (T)^0.5
   g = ((1 - rho13^2) / (1 - rho12 ^2- rho23 ^2- rho13 ^2+ 2 * rho12 * rho13 * rho23) ^0.5
   sum = 0
   For i = 1 To nSimulations
         St1 = S1  # Clear Price
         St2 = S2  # volume MWh
         St3 = S3  # Bid price £/MWh
          #  Halton function is a Quasi Random Number Generator
         # BoxMuller function when used in combination with the Halton function generates
              random numbers more randomly  than usual random generator function.
         Epsilon1 = BoxMuller(Halton(i, 3), Halton(i, 5)
         Epsilon2 = BoxMuller(Halton(i, 7), Halton(i, 11))
         alpha2 = rho12 * Epsilon1 + Epsilon2 * (1 - rho12 ^ 2) ^0.5
         alpha3 = BoxMuller(Halton(i, 13), Halton(i, 15)) / g + (rho23 - rho13 * rho12) *
         Epsilon2 + rho13* Epsilon1 * (1 / (1 - rho12 ^2)) ^0.5
         St1 = St1 * exp(Drift1 + v1Sqrdt * Epsilon1)
         St2 = St2 *exp(Drift2 + v2Sqrdt * alpha2)
         St3 = St3 * exp(Drift3 + v3Sqrdt * alpha3)
         st2b = min(S2, St2) # volume
         sum_payasbid = sum + + max(z * (St1 * st2b - st2b * St3 - X), 0)    # pay as
```

```
            bid >>  max [ 0,VMWh * Pclear - VMWh*Pbid – X]
        sum_pay%clear = sum + max(z * ((St1 * st2b*margin) - X), 0)    # pay % of clear
            price  >>           max [ 0,(VMWh * Pclear )*margin – X]
        sum_payfixed = sum + max(z * (St1 * st2b - st2b * Pfixed - X), 0)    # pay as bid
            >>    max [ 0,VMWh * Pclear - VMWh*Pfixed – X]

Next i
AssetValue_payasbid  = exp(-r * T) * sum_payasbid / nSimulations   # value Pay as bid
AssetValue_pay%ofClearPrice  = exp(-r * T) * sum_pay%clear / nSimulations   # value
  Pay % of  clear price
AssetValue_payfixedprice  = exp(-r * T) * sum_payfixed / nSimulations   # value Pay
  fixed
```

Appendix E: Array Representations within PyEMLab-Agg

Arrays are represented in Numpy matrices within the PyEMLab Aggregator model. Use of Numpy arrays allows for vectorization as well as data-slicing on various parameters and results in simulations at a much higher speed. It allows fast filtering of data such as all contracts associated with "aggregator 5" that have cleared and have a bid price less than £105/MWh.

The following figures are excel representations of some of the more important arrays used in the simulation presented in this thesis. These excel representations were used to design the arrays required for this simulation.

Note the # symbol is used to represent "number".

Repository Package ("Repo")

The repository package enables the simulation to store in-memory data that is used by a variety of different agents. Results are stored in arrays in the "repo" and are used later in analysis and output. Note hypothetical data is provided in the examples below.

E.1 Current Aggregator Offers to Customers

							eg might want to offer diff contracts to diff customer types			
					contract terms		customer type			
0	1	2	3	4	5	6	7	8	9	10
Agg Number	start yr month	Contract length Months	Contract type	margin	Bid min	FP	customer type	cluster type		
1	23	12	0	0.5						
1	12	12	0	0.5						
1	0	12	1		0					
			2			123.55				

Figure E-1: Aggregator contract offers array

E.2 Bids to Aggregator from Domestic Customers

						0 - dome 1 = ind		gen 2						
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
ID for Bid	Agg#	Bid P	Bid Vol	Customer Bid seg	Cleared %	Cust type	Actual Volume	profit agg	Revs Cust	Contract Type	margin%	price bid min	Price fixed	FAKE INDX
1	1	200	5	0-9 or -1 -10	0	0					0.5	100		
2	1	200	5		1	0					0.3			
3	1	123	3		1	0					0.2			
4	2	85	2		1	0								
5	2	45	1		0.8	0								

Figure E-2: Customer bids to aggregator array

E.3 Propagation Matrix Customer to Customer

Customer ID	Agg number	Good stim	Bad stim	send msg to	prob of RX	On/off	Final Good Rx	Final Bad RX	Code Unique
1	0	0.3		2222	0.5	1	0.3	0	1
2	0	0.5	0.1	1254	0.5	0	0	0	2
1	3	0.1	0.6	85	0.5	1	0.1	0.6	3000001

Figure E-3: Propagation array

E.4 Aggregator Flex Bid Matrix - Bids by Bucket

	Bucket Number>>	0	1	2	3	4	5	6	7	8	9
0	Price low	2	15	24	36	38	44	54	55	85	95
1	Price High	15	24	36	38	44	54	55	85	95	96
2	Volume Kwh Total	4444	66666	5555							
3	Bid max of buckets	15	24	36	38	44	54	55	85	95	96
4	Bid weighted buckets	10.5	16.8	25.2	26.6	30.8	37.8	38.5	59.5	66.5	67.2
5	Vol pay as bid										
6	Average bid price of customers paty as bid										
7	volumes pay as clear										
8	Average bid price of customers paty clear	3.7	3.7	3.7	3.7	3.7	3.7	3.7	3.7	3.7	3.7
9	Volume of pay fixed										
10	Average price of customers pay fixed	12	15	34	64	84	24	55	61	66	69
11	Vol of dom Customers ???										
12	Volume of Ind ???										
13	clear fraction	1	1	1	0.8	0	0	0	0	0	0
14	Final bid price	9.41	20.96	31.34	29.40	28.05	35.24	44.81	47.51	64.55	75.82
15	Weighted margin of bid	0.2	0.1	0.7	0.3	0.5	0.5	0.55	0.3	0.21	0.4

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
ID for Bid	Agg/Gen number	Bid P	Bid Vol	Customer Bid seg	Cleared %	type	actual voll	Spare	Spare	Spare	Spare	Spare	Spare	Spare
1	1	200	5	0-9 or -1 -	0	2								
2	1	200	5	1	1	2								
3	1	123	3	2	1	2								
4	101	85	2	3	1	500								

Figure E-4: Aggregator bid buckets array

E.5 Bids to ISO by Aggregators/Generators

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
ID bid	Agg	strat yr	Customer cluster membership (SPSS)	Contract renewal month	Contract length Months	Expecatation pound per yr	Cleared	Volume bid	Contract type	margin	Bid min	FP	Revs agg	revs customer	tick	next expiry mnth
1	1	0	4	0	12	100	1	1	0	0.5						12
2	1	0	1	0	12	250	1	2	0	0.5						12
3	1	0	4	0	12	150	1	2	1		0	100				12
4	1	0	1	0	12	0	1	2	1		0					12

Figure E-5: Bids to ISO array

E.6 Customer Contract Database

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
ID bid	Agg	start yr	Customer cluster membership (SPSS)	Contract renewal month	Contract length Months	Expecatation pound per yr	Cleared	Volume bid	Contract type	margin	Bid min	FP	revs agg	revs customer
1	1	0	4	0	12	100	1	1	0	0.5				
2	1	0	1	3	12	250	1	2	0	0.5				

15	16	17	18	19	20	21	22	23	24	25	26	27	28
tick	next expiry mnth	in market	bidup MC base	Bid Down MC Base	bid up Current	bid Down Current	Current Vols contract yr	current revs contract yr	Volume up max	Volume down max	Volume up bid actual	Volume bid Down Actual	Zip up factor
	12	1	324										
	12	1											
	12	1											

29	30	31	32	33	34	35	36	37	38	39
Zip down	Customer type	learning method	flexpot	cust vol var	customer underbid factor	Weekly cust Revs	Weekly Vol bid total	Weekly Vol accepetd total	Weekly aggs Revs total	latest target p
		not used		0.2		15	11	11	15	
		eg 0 = MC		0.3		32	11	8	23	
						34	12	12	33	

Figure E-6: Customer contract and bid matrix

E.7 Profit and Loss Accounts

Aggregators keep track of their profit and loss accounts and use such data to adjust bids and to determine at the end of the year whether they are to change business model or to exit the market. P&L's are kept for each aggregator company daily monthly and yearly. Note COS – is cost of supply – that is the payments made to the customers supplying flex + the cost of hedging.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Period	Revs	cos	opx	Depr	Gross proit	Tax	profit post tax	ROE	Proit margin%	COS Customer	Hedge cost	Revs Custs	Revs Hedged	CPX	Equity
1	1200	500	500	33	167	33.4	133.6	37%	11%	500	0	1200	0	330	363
2	800	350	400	33	17	3.4	13.6	4%	2%	350	0	800	0	330	363
		Cos = Cos direct + hedge cosrt													
		Revs = Revs hedged +Revs Custs													

Figure E-7: Aggregator profit and loss account; internal

As in the real world, "yearly accounts" are broadcast to all agents one year after accounting year-end (i.e. placed into the public domain via government reporting agencies).

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
end of year											at end of year			
Yearnumber	AggID	Revs	COS	OPX	Depr	Profit pre tax	Profit post tax (Net Inc)	Profit margin	Average CP	Average bid	N Dom customers	N Ind	N total	Spare
0	1	1,800,000	516000	100000	100000	1,084,000	867200	0.481778	300	86	3000	4000	7000	
0	2	4,800,000	1024000	100000	100000	3,576,000	2860800	0.596	300	64				
1	1	204,000	46000	100000	100000	-42,000	-33600	-0.16471	102	23				

15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
								lets assume one month of COS								
Average customer s during yr approx	Spare	calc avg bid based on yr end	Bal sheet items	Assets	Equity	asset turnover revs / Assets	debt to ewuity	Current ratio total assets by liabilities	ROE	ROA	ROCE	Profit margin	Hedged Revs	Normal Revs	Hedge cost	Normal COS
6000		86		1.20E+06	1.20E+06	1.500		0.97	72%	0.72	0.94					
16000		64		1.20E+06	1.20E+06	4.000		0.93	238%	2.38	3.21					
2000		23		1.20E+06	1.20E+06	0.170		1.00	-3%	- 0.03	- 0.04					

Figure E-8: Aggregator profit and loss account: Public domain (seen by others)

E.8 Domestic Customer Agent_Zero Disposition Matrices

Used to keep account of the agent_zero scores associated with Disposition D, affective (emotional) V, Social S, and logic scores P for each of the 50,000 customer agents. Disposition D is the weighted average score of V, S and P.

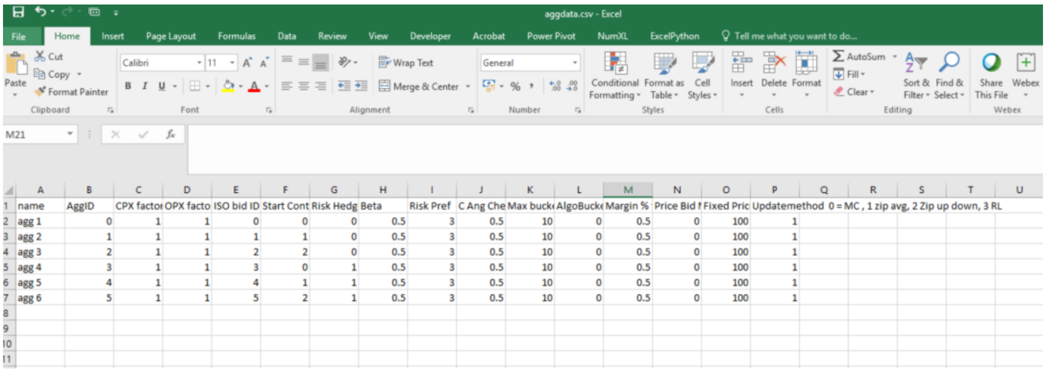
0	1	2	3	4	5	6	7	8	9	10	11	
customerID	Current agg #	V	S	P	wtV	Wt P	Wt S	D	Vangry	Vhappy	Dummy index	Ex
1	1	-0.3	0	0	0.333	0.333	0.333	-0.0999	-0.6	0.3	0	
2	1	0	0	0	0.333	0.333	0.333	0			1	

12	13	14	15	16	17	18	19	20	21	22	23
Expectation for yr	Custome r revs/yr	Customer class	stim happy	stim angry	Ticks so far in my yr	?	look at other offers	cant stand agg	in market flag	Accepted Vols	target price expected
100	25	1					??				

Figure E-9: Domestic customer Agent_Zero disposition matrices

Appendix F: Example Input Data from CSV Files

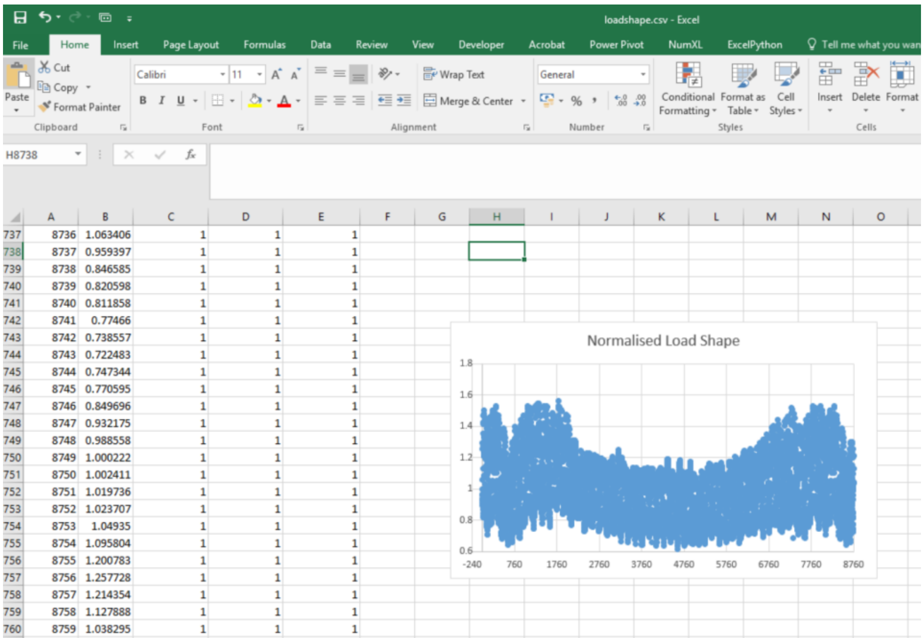
F.1 Aggregator Input Data



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	name	AggID	CPX factor	OPX facto	ISO bid ID	Start Cont	Risk Hedg	Beta	Risk Pref	C Ang Che	Max buck	AlgoBucke	Margin %	Price Bid	Fixed Pric	Updatemethod	0 = MC , 1 zip avg, 2 Zip up down, 3 RL
2	agg 1	0	1	1	0	0	0	0.5	3	0.5	10	0	0.5	0	100	1	
3	agg 2	1	1	1	1	1	0	0.5	3	0.5	10	0	0.5	0	100	1	
4	agg 3	2	1	1	2	2	0	0.5	3	0.5	10	0	0.5	0	100	1	
5	agg 4	3	1	1	3	0	1	0.5	3	0.5	10	0	0.5	0	100	1	
6	agg 5	4	1	1	4	1	1	0.5	3	0.5	10	0	0.5	0	100	1	
7	agg 6	5	1	1	5	2	1	0.5	3	0.5	10	0	0.5	0	100	1	

Figure F-1: Aggregator input file

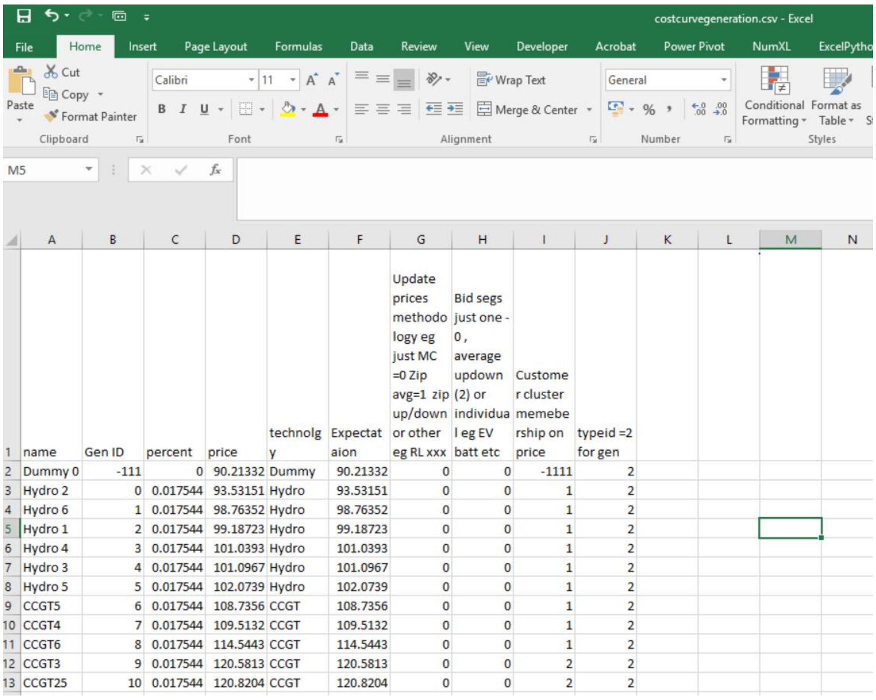
F.2 Demand Shape CSV File



	A	B	C	D	E
737	8736	1.063406	1	1	1
738	8737	0.959397	1	1	1
739	8738	0.846585	1	1	1
740	8739	0.820598	1	1	1
741	8740	0.811858	1	1	1
742	8741	0.77466	1	1	1
743	8742	0.738557	1	1	1
744	8743	0.722483	1	1	1
745	8744	0.747344	1	1	1
746	8745	0.770595	1	1	1
747	8746	0.849696	1	1	1
748	8747	0.932175	1	1	1
749	8748	0.988558	1	1	1
750	8749	1.000222	1	1	1
751	8750	1.002411	1	1	1
752	8751	1.019736	1	1	1
753	8752	1.023707	1	1	1
754	8753	1.04935	1	1	1
755	8754	1.095804	1	1	1
756	8755	1.200783	1	1	1
757	8756	1.257728	1	1	1
758	8757	1.214354	1	1	1
759	8758	1.127888	1	1	1
760	8759	1.038295	1	1	1

Figure F-2: Demand input file

F.3 Generator Input Data



name	Gen ID	percent	price	technolgy	Expectation	Update prices methodology eg just MC =0 Zip avg=1 zip up/down or other eg RL xxx	Bid segs just one - 0 , average updown (2) or individual eg EV batt etc	Customer cluster memebership on price	typeid =2 for gen
Dummy 0	-111	0	90.21332	Dummy	90.21332	0	0	-1111	2
Hydro 2	0	0.017544	93.53151	Hydro	93.53151	0	0	1	2
Hydro 6	1	0.017544	98.76352	Hydro	98.76352	0	0	1	2
Hydro 1	2	0.017544	99.18723	Hydro	99.18723	0	0	1	2
Hydro 4	3	0.017544	101.0393	Hydro	101.0393	0	0	1	2
Hydro 3	4	0.017544	101.0967	Hydro	101.0967	0	0	1	2
Hydro 5	5	0.017544	102.0739	Hydro	102.0739	0	0	1	2
CCGT5	6	0.017544	108.7356	CCGT	108.7356	0	0	1	2
CCGT4	7	0.017544	109.5132	CCGT	109.5132	0	0	1	2
CCGT6	8	0.017544	114.5443	CCGT	114.5443	0	0	1	2
CCGT3	9	0.017544	120.5813	CCGT	120.5813	0	0	2	2
CCGT25	10	0.017544	120.8204	CCGT	120.8204	0	0	2	2

Figure F-3: Generator input file

Appendix G: Clustering of Customer Data

To aid in later analysis Customer input data was clustered using SPSS [194, 589] clustering tools. Output from this process is summarized below. Data from the analysis was used as an input to customer agents, so that data could be summarized for later analysis by customer class.

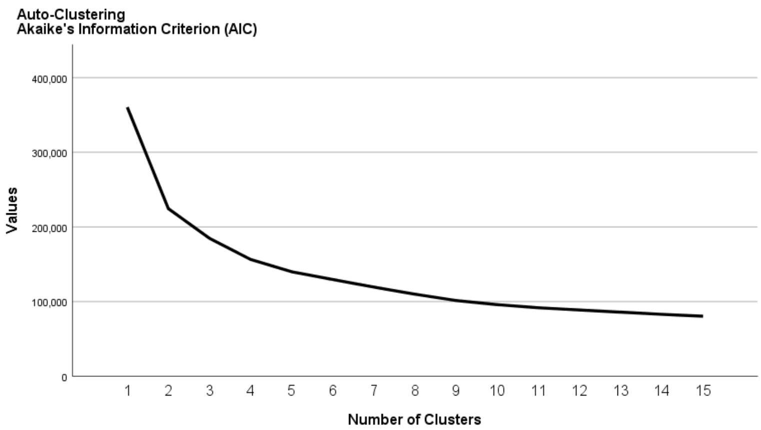


Figure G-1: AIC vs number of clusters; Customer input f=data for flex

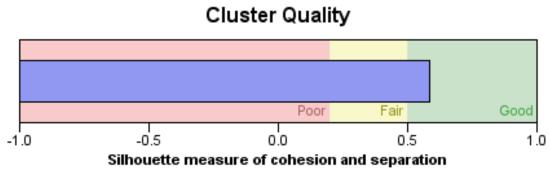
Akaikes Information criterion (AIC) provides a measure of the quality of models for a given set of data. The lower the number the better the model. According to Figure G-1, one might pick 9 or 10 clusters to reduce the AIC factor to an acceptable level. However, with 10 clusters it was found that it was difficult to theorize about the various differences in cluster. As a general rule of thumb, typically researchers use 2 - 5 clusters, as it is easier to explain the meaning of cluster membership. An analysis of five clusters is therefore presented below using output from SPSS 25.

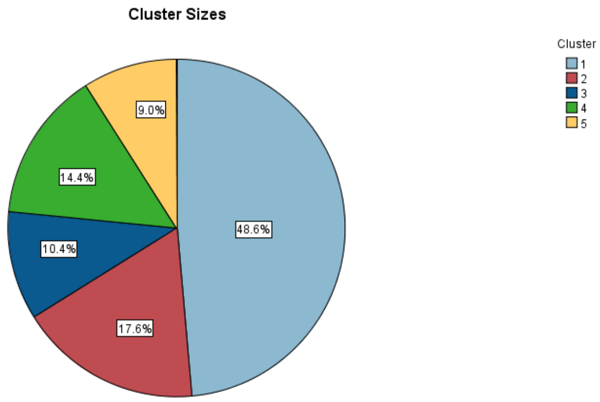
G.1 Overview of Customer Clusters

The five clusters were extracted from the input data using a 2-step clustering process. The results and the various distributions are summarized below.

Model Summary

Algorithm	TwoStep
Inputs	10
Clusters	5





Size of Smallest Cluster	4706 (9%)
Size of Largest Cluster	25248 (48.6%)
Ratio of Sizes: Largest Cluster to Smallest Cluster	5.37

Figure G-2: Customer cluster sizes and distribution

G.2 Relative distributions

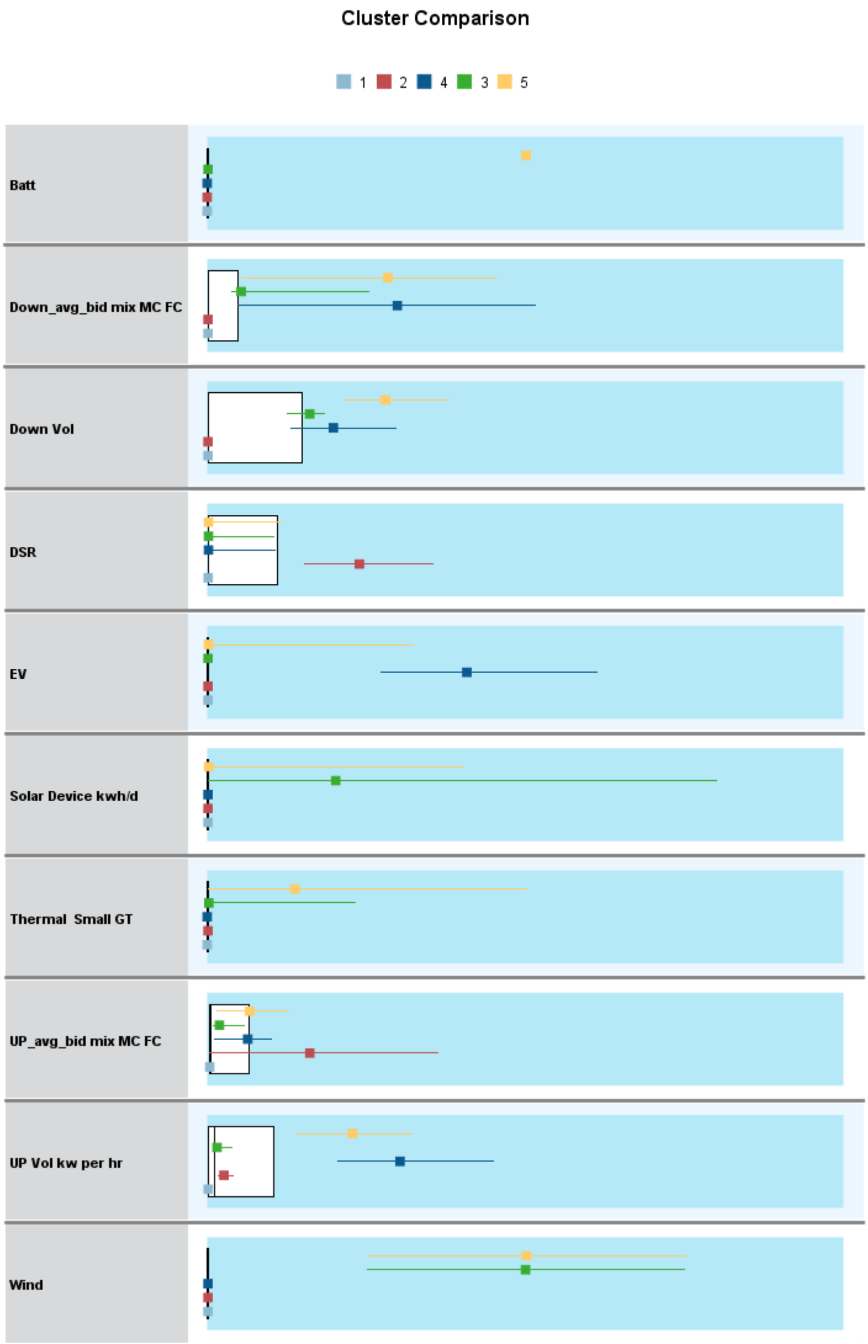


Figure G-3: Customer cluster comparisons using Box-Whisker plots

G.3 Categorization of Customer Clusters

Cluster Number	Description
1	Everything Low (bids & Volumes)
2	High DSR flex, everything else low
3	High Solar and High Wind flex
4	High Volumes of EV flex
5	High Battery Thermal and Wind flex

Table G-1: Categorization of customer clusters; Description

Note about 50% of those customers in Cluster 1 would be considered as customers in fuel poverty.

Appendix H: Class Diagrams

As this is a large package only a selection of class diagrams are shown. An “m” in a pink circle refers to methods and “f” in a yellow circle to fields.

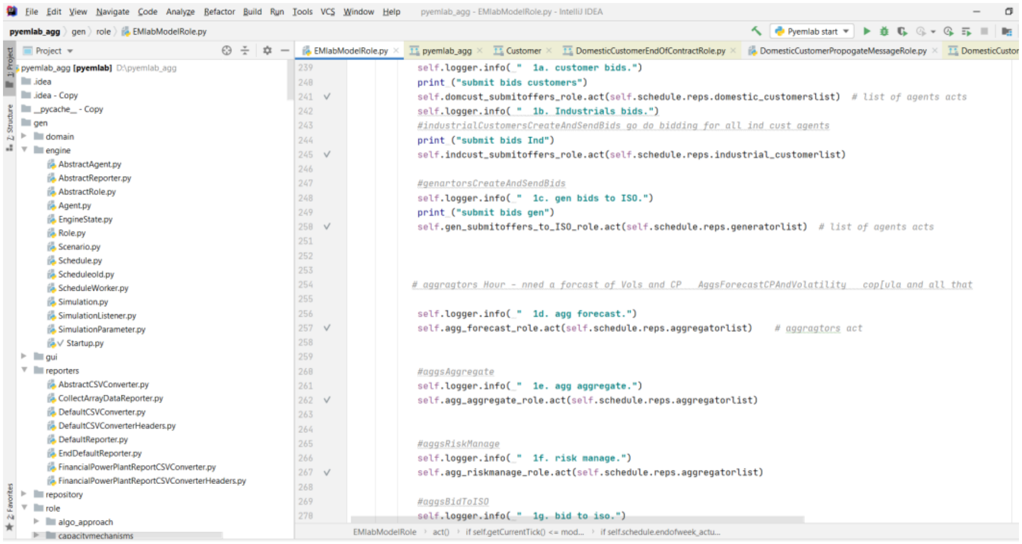
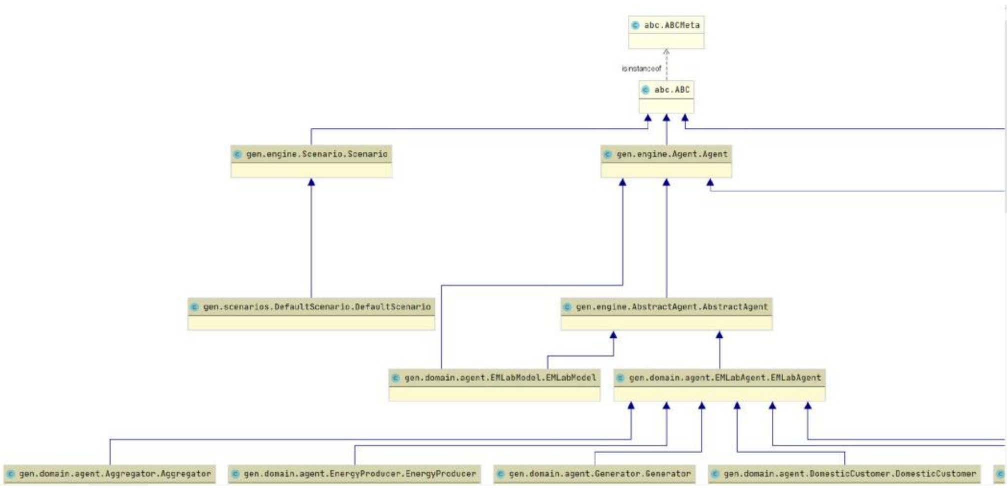


Figure H-1: Code overview



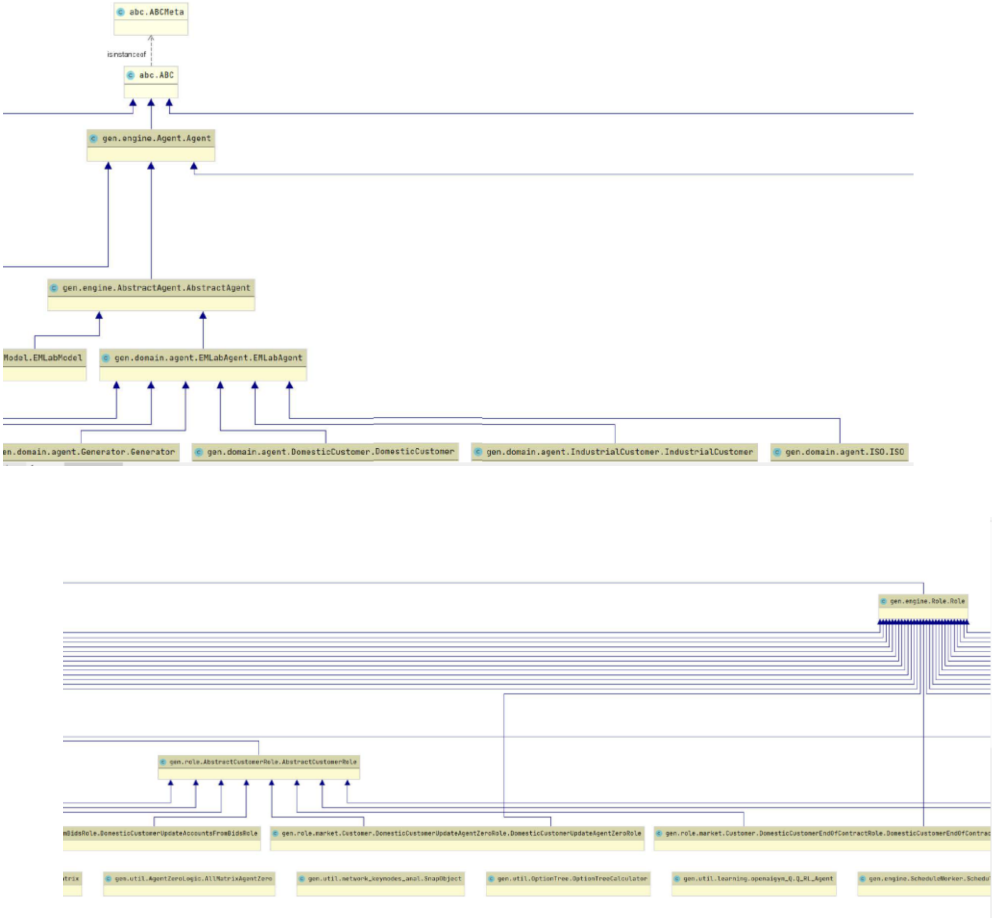


Figure H-2: Class diagrams – Overview

H.1 Domestic Customer Agent

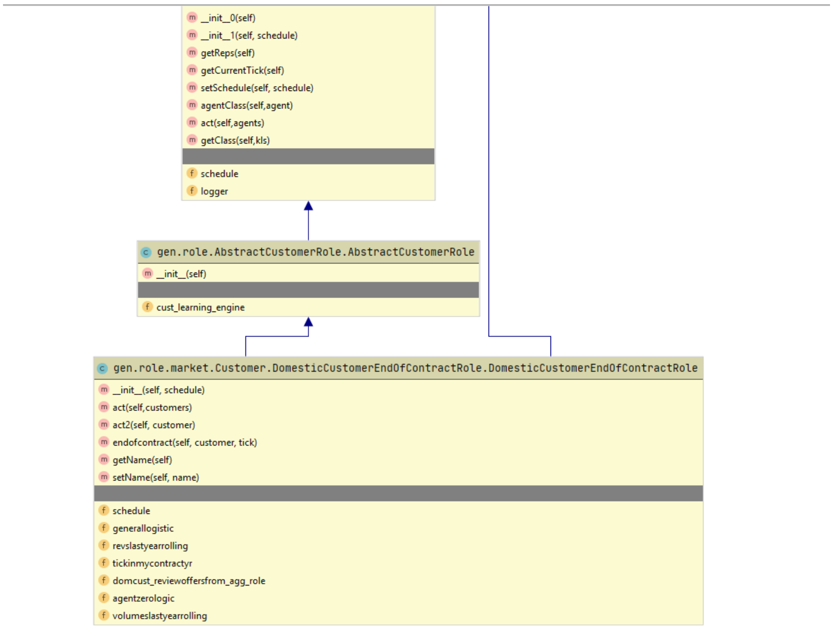


Figure H-3: Class diagrams – Domestic Customer agent

H.2 Current Aggregator Offers to Customers

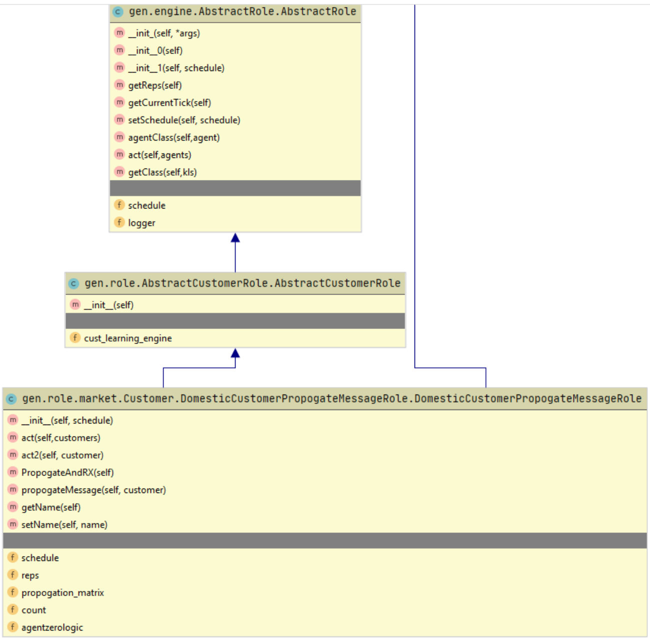


Figure H-4: Class diagrams – Aggregator offer to customers

H.3 Bids to aggregator from Domestic Customers

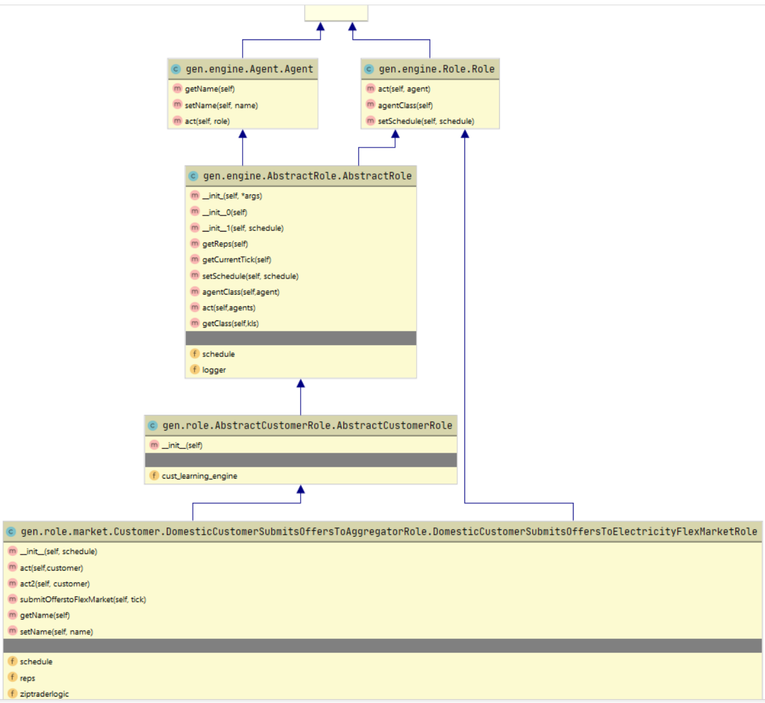


Figure H-5: Class diagrams – Bids to Aggregator

H.4 EMLabRole

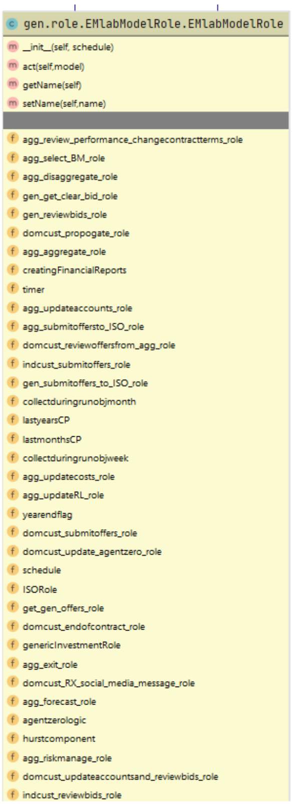


Figure H-6: Class diagrams – EMLabRole

H.5 Aggregator Flex Bid Matrix - Bids by Bucket

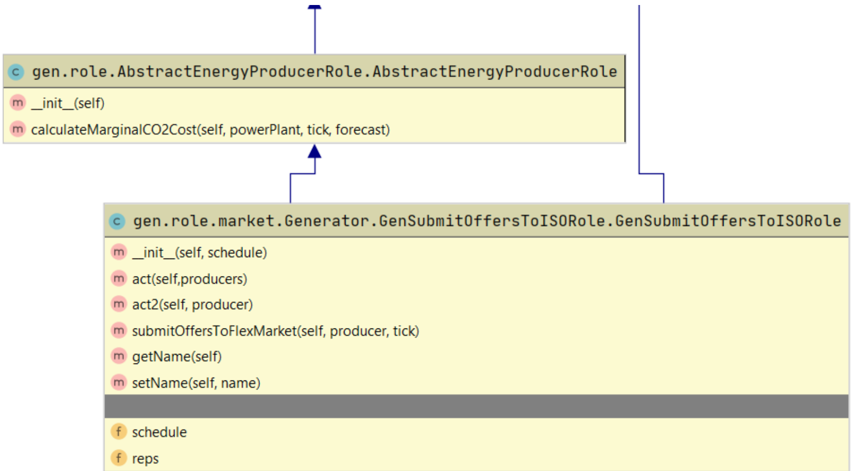


Figure H-7: Class diagrams – Bidding

H.6 Bids to ISO by Aggregators/Generators

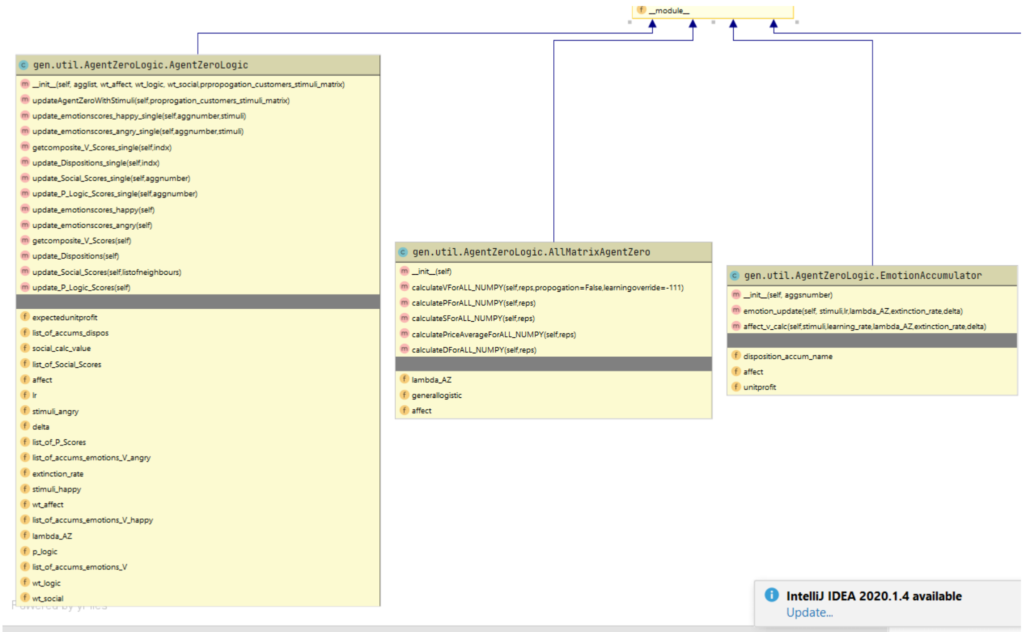


Figure H-8: Class diagrams – Bids to ISO

Appendix I: Aggregator: Selection of Business Models at Year End

At the end of each calendar year, (31st of December) aggregators assess their performance and consider changing business model. A forecast of future performance for the various business models (six in this case) is performed. Note in a future iteration of the simulations, calendar years will be allowed to start at any point in the year e.g. 31st July as opposed to 31st Dec. Currently a “naïve” forecast of Clearing Price (CP) is carried out using last year’s CP as a predictor of the future.[291]

Although NPV could be used to assess future economic performance, in the current model a profit margin comparison has been performed. It is expected that with the assumptions made the two approaches will be broadly similar. Profit margins equations for the three base business models are provided in equations ((I-1) – (I-3) below. Risk is accounted for using the Ang, Chen and Sundaresan model discussed in Chapter 5 (equation (5-12)).

$$\text{Pr}ofit\_Pay\ \%\ clearing\ price\,\pi_{percent} = \frac{(P_{clear} * Vol_{mwh} * margin - Depr - OPX) * (1 - taxrate)}{(P_{clear} * Vol_{mwh})} \quad (I\text{-}1)$$

$$\text{Pr}ofit\_Pay\ bid\ price\ \pi_{percent} = \frac{((P_{clear} - P_{bid}) * Vol_{mwh} - Depr - OPX) * (1 - taxrate)}{(P_{clear} * Vol_{mwh})} \quad (I\text{-}1)$$

$$\text{Pr}ofit\_Pay\ \text{fixed}\ price\ \pi_{percent} = \frac{((P_{clear} - P_{fixed}) * Vol_{mwh} - Depr - OPX) * (1 - taxrate)}{(P_{clear} * Vol_{mwh})} \quad (I\text{-}2)$$

Where:

P_{clear} - *Expected clearing price in market £/MWh*

---

[291] The actual methodology looks at clearing prices associated with the upcoming demand. It uses CP/demand data with a lookback horizon of 1 year from the current tick.

P_{bid} - *Average expected bid price*

$margin$ - *Aggregators margin %*

$P_{fixedprice}$ - *Fixed price offered £/MWh*

Vol_{mwh} - *Average volume of customers (MWh)*

$Depr$ - *Yearly depreciation*

OPX - *Yearly Operating costs*

$taxrate$ - *Corporate tax rate*

The new Business Model for the ensuing year is found by comparing the values provided by equations above with adjustment for risk[292].

[292] The maximum utility value is chosen. Expected profit along with expected volatilities and the value of risk (if appropriate) are used to calculate a utility for each business model using the Ang, Chen and Sundaresan model.

Appendix J: Agent Model Description ODD Protocol

ODD Model description

The agent based model presented herein is described in accordance with the ODD (Overview, Design concepts, and Details) protocol [525-527]. In addition Müller et al., [625] extended the ODD methodology to include for human decision making (ODD D+ (decision plus)). Although this thesis does not strictly follow the additional categories outlined in ODD D+, descriptions are added where it was felt appropriate[293].

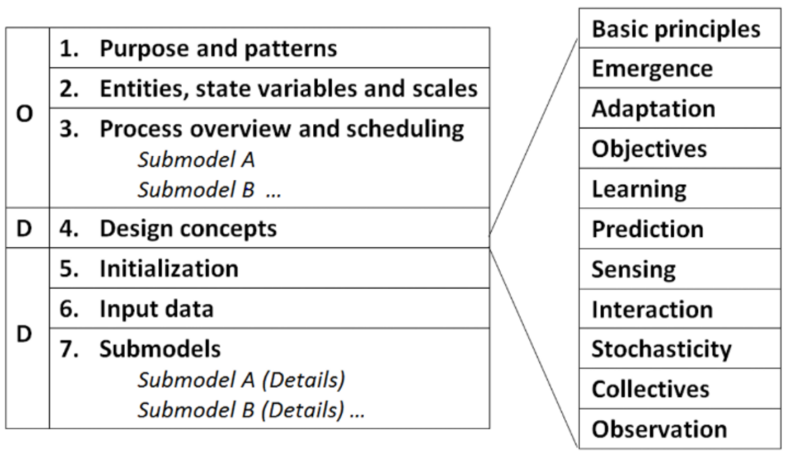


Figure J-1: ODD framework: Reproduced from Fig 1 from [528]

The ODD framework description for the current PyEMLab-Agg is given below:

1. Purpose: This model has been developed to simulate a low-carbon distribution network where customers provide flexibility via a bidding market managed using

[293] Mainly on agent decision making.

aggregators and an ISO. The effect of corporate behaviour (aggregator companies with risk management) and more human like customers (emotional and bidding behaviours) have been included to provide a more holistic view of how this market might operate in the future.

2. Entities, state variables, and scale: In this model, agents are individual households (domestic customers), small and medium sized entities (industrial customers), aggregator companies, generators and the Independent System Operator (ISO).

Domestic Customer agents are characterized by the state variables: identity number, marginal cost (for Up and Downward volumes – this is a starting value), up and downward flexibility volumes (MW), expectation for yearly revenues (£ per year), cluster ID number (type of customer e.g. affluent with 2 EV's, or customer with limited flexibility), contract types and conditions e.g. price payment terms. Revenues from biding per contract year (running totals) are also stored, as well as the last bid (volumes and price). Domestic customer agents keep track of their emotional state about particular aggregators using an Agent_Zero framework described in section 6.4 of the thesis. They can also change contracts with Aggregator agents yearly.

Industrial Customer agents are characterized by the state variables: identity number, marginal cost (Up and Downward), up and downward flexibility volumes, current aggregator and contract terms with aggregator. They are similar to Domestic Customer agents, but do not utilize the Agent Zero logic and do not change Aggregators during the course of the simulation, nor contract type. They simply bid at marginal costs and volumes.

Aggregator agents are characterized by the state variables: identity number, name, latest contract offers, capital and operating costs, portfolio bucket volumes, bidding prices for aggregation and disaggregation. The number of up/down bid buckets, option/hedging values, clearing price forecasts, price volatility values and various status flags/values such as Risk/Hedging on, a risk aversion factor and the current business model. Aggregators keep an account of their costs and revenues generated using an internal set of matrices (P&L matrices).

ISO agents are characterized by the state variables: identity number, name of ISO, reserve volume % and Volume of lost load (VOLL) value. In the current simulation, only one ISO agent is present. Its primary purpose is to "clear" the market, store bids and inform bidders (aggregators and other larger entities such as generators) of their winning bids in the market and to pay them as necessary. In the current simulation, the ISO does this at zero cost.

Generator agents represent large generation assets i.e. power plants of different types and associated costs. Costs are fixed at the beginning of the simulation. Agents are characterized by the state variables: identity number, generator name, technology type, Marginal cost (Up and Downward), up and downward flexibility volumes, expectation for yearly profits (£ per year) and an update price methodology (a number which is used to determine how bidding prices will be updated). A record of the revenues and profits generated from bidding are included in a set of profit and loss matrices.

3. Process overview and scheduling— In this model, users control the process by using a python scripting language that specifies what procedures/modules need to be run and in what order. Users can therefore run the model with and without social message propagation for example. The base model uses the following procedures that are run hourly, weekly, monthly and yearly as described in more detail in Chapter 7 of the thesis.

Initialization

- *Read in customer (Industrial and Domestic), aggregator, generator, flex demand data from CSV files.*
- *Create and Initialise agents using Agent Factory's*[294]
- *Initialise various in-memory arrays to store data.*

Hourly

- *Domestic Customers Create And Send Bids to its current aggregator*
- *Industrial Customers Create And Send Bids to its current aggregator*
- *Generators Create And Send Bids directly to ISO*
- *Aggregators forecast future price volatilities and clearing price probabilities based on historical data*
- *Aggregators aggregate bids from Industrial and Domestic customers into multiple buckets e.g. 10*
- *Aggregators Risk Manage – estimate risk of each bucket and decide whether to hedge. Calculate and account for cost of hedge*
- *Aggregators send bucket bids to ISO*
- *ISO takes bids and clears the market using economic dispatch – and calculates a clearing price where demand = supply. ISO sends out cleared bids (i.e. bucket bids and generator bids) that have been accepted.*

[294] The factory pattern [626] is a common design pattern to create objects. The objects in this case are a collection of heterogeneous agents.

- *Aggregators disaggregate: Takes cleared bids and apportions these cleared bids to the various customers. Accounts for payments to individual customers. Model assumes instant payment.*
- *Generators update accounts of cleared bids*
- *Aggregators Update Accounts (daily monthly) & use Zip trader algorithm to adjust future bids*
- *Customers (industrial and domestic) process Cleared Bids and update internal accounts of agents*
- *Update customer zip trader to enable adjustment in customer bid level*
- *Update generator bids and accounts*

Weekly

- *Update Customers Agent_Zero (AZ) modules – Updates emotions etc.*
- *Propagate Messages (Social Media) to connected agent (if thresholds in customer AZ module are met).*
- *Calculate Hurst exponents and Store*
- *Collect dispositions etc. and Store weekly stats*
- *Update propagations and effects on Agent Zero models within Agents*

Monthly

- *Update Agent_ Zero Scores using Social Scores from other connected agents*
- *Aggregators review performance of existing contract and choose new contract type and terms if applicable*
- *If domestic customer is due to renew the customer compares and selects from aggregator offered Contracts.*
- *Calculate elasticity Impact on monthly demand by comparing last months average Clearing Price with this months*
- *Collect monthly stats and store*

Yearly

- *Assess aggregator yearly performance and aggregator checks for market exit*
- *Aggregator Business Model (BM) Assessment And Selection change BM*
- *Calculate yearly elasticity effect on demand*
- *At end of simulation, store various in-memory matrices into hdf5 database.*

The model synchronously updates. All agents bid at the same time and currently order does not matter. Each simulation time step represents 1 hour. Simulation steps occur every hour for five years.

4. Design concepts

Emergence: Emergent phenomena are expected to be seen in this model as it is a complex simulation that includes adaptive behaviour with emotions. The use of Hurst coefficients/exponents have been used to detect such emergent behaviour.

Adaptation: Agents adapt to changing prices and offers made to them by aggregation agents. Social media in the form of a network is used to transport messages to from connected domestic agents. Messages on aggregator performance as well as price bidding information is used.

Objective: Different agents have different objectives. In this model These are summarized in Table J-1.

Agent Type	Objective
Domestic Customer	To achieve its expected yearly revenues (an input), or to follow clearing prices if this is higher. Daily bids are adjusted using Zip Trader Algorithm (section 6.2.3).
Industrial Customer	To bid its marginal cost as per input assumptions. This is provided to the simulation using an input file (CSV).
Generators	To bid its marginal cost as per input assumptions. This is provided to the simulation using an input file (CSV).
Aggregator	1/To maximise its profits and also to meet minimum Return on Equity Target over the year. Daily bids are adjusted using Zip Trader Algorithm (section 6.2.3). Target prices are set in a manner discussed below. 2/ To apportion bids into 10 buckets or bins so that it maximises its profits under different contract terms. 3/ To select at year end, an appropriate Business model that will provide the greatest economic value to the Aggregator. 4/ To adjust contract terms monthly (for new contracts) to maximise profits.
ISO	Simply to clear the market using an Economic dispatch algorithm. Future work will include an AC OPF formulation which will be used to clear the market at minimum cost.

Table J-1: Agent objective summary

Interaction: Domestic Agents who are connected via some form of social group, represented as a social network, can interact with each other. Different networks are able to be assigned to the model and affects propagation mechanics and results output. Every hour/week/month (timeframe can be changed), domestic customers agents interact by sharing bid price information and their views on their current aggregator with their neighbours.

Aggregator Agents "capture" domestic customers by advertising contract details monthly, prices type of contract etc. Domestic customers evaluate said contracts at the end of their contracts and based on this may choose to change their aggregator relationship e.g. leave the current one for a new one with a contract with better terms. Only a certain proportion of the agents reach the end of their contract in any one month and is based on OFGEM data on contract renewals throughout the year.

Aggregators collate bids from domestic and industrial customers and package these bids into a number of buckets – Ten[295]. That is the aggregator presents ten bids to the ISO. These bids are submitted to an ISO agent who also receives bids from generator agents. The ISO agent clears the market and notifies aggregator and generator agents of the current clearing price and the volumes that were accepted. In some cases some of the aggregator buckets bid might not be cleared.

Learning: Agents use a ZIP Trading algorithm to alter their bid prices. In the case of Domestic customers, the ZIP algorithm uses a set point (target) that is a combination of past clearing prices and expectations about revenues. The customer agent has a view on what level of revenues it wishes to earn over the year (input data driven), but will also be swayed by the value of the recent historical clearing prices.

In the case of the aggregators, they estimate setpoint/target prices that should 1/ cover their operating and capital costs and 2/ provide them with the maximum profit.

Aggregators also collect data during the simulation and use optimization routines

[295] This can be changed.

to change their offers to domestic customers. These offers represent potential new contracts. In the current simulation Generators, Industrial customers and the ISO agent have no learning abilities, although this can be easily extended.

Decision-making: Currently only the Aggregator and Domestic Customer agents, are making decisions during the simulation. This is summarized in J-2.

Agent Type	**Decision**	**Description**
Aggregator	Risk management Infrastructure Investment	Whether to pay for additional equipment/hardware if not already risk managing
	Hedge	Whether to pay for the cost of the hedge and buy an option to cover potential revenue reductions
	New Business Model	At year end; decides on whether to change its business model. One of six - Revenue generation model and risk management stance
	Contract Terms	Decide on the contract terms to offer to new and expiring customers- uses optimization to decide on price terms and contract type. Changes monthly
	Bucket Bid Price	Adjusts bucket bids using a ZIP trader algorithm adjustment factor
	Bucketing Algorithm	Current runs are fixed with one type but some options allow for the number of buckets to be changed during the simulation. The Bucket edges e.g. 20-60 £/MWh; 61 -200 etc. are apportioned during the bucketing process using predictions of clearing price
	Exit Market	After X years of losses whether or not to exit the market
Domestic Customer	New contract	At end of existing contract, choose from offers from the various aggregators or not at all
	Bid Price	Uses previous or base marginal costs for flexibility adjusted by a factor which is adjusted using a ZIP trader algorithm

Agent Type	Decision	Description
Domestic Customer contd.	Exit market	If after x years of not meeting customer expectations whether to leave the market or not
	Volume of flex to bid (option)	Currently all sims use the max volumes of flex. The model is able to adjust those volumes. E.g. should a customer only supply 50% of the max volumes

Table J-2: Decision-making in key agent types

Prediction. To evaluate and choose bucketing ranges (bin sizes for aggregation) the aggregator uses historical data to estimate a probability distribution function (PDF) of clearing prices. This PDF is used to apportion bids to buckets so that the Agent is likely on a probabilistic basis to maximize its revenues.

Sensing: Agents update emotions based on the interactions with other agents on a social network. Clearing prices produced by the ISO from economic dispatch of power are broadcast to all agents, who can analyse such data to improve bids. This data is used by the ZIP trader routines. Aggregators also publish their new contract terms monthly (type and values) and are shared with domestic customers – who use such data to assess whether they would like to take a new contract.

Stochasticity: The bidding algorithms used by the various agents have a random element within them. Analysis has shown that clearing prices could have a variability of +- £5-15/MWh dues to such random fluctuations.

Current Customer input data has been randomised. For example, expectations, Customer location on social network randomized.

Propagation of messages between domestic customer agents depends on probabilities associated with an emotion value stored within the agent. Higher emotion values have a higher probability of being sent. A base receive probability of 30% is used[296]. That is, if a random number is <=30% messages sent by connected agents over a social network will be received and processed.

Observation: Data is collected and collated into in-memory arrays and output into an hdf5 database at the end of the run. Data collected includes around 50 sets of variables some stored as three-dimensional arrays so that data is split by customer type and by aggregator. Histograms and distributions of contract terms (e.g. prices, margins) are also collected through time. Agent_Zero values for key agents are also collected.

Data output and trends have been plotted using Excel, although software packages such as Miner3D [627, 628], SPSS [194, 587, 589] have also been used.

5. Initialization: A total of 50,000 Domestic customer agents, 4500 Industrial customer agents, 59 Generator agents and six Aggregator agents were created, using Agent Factories. Agents' characteristics were initialized with data collected for households' locations and socioeconomic characteristics. Model parameters such as simulation length, time steps, propagation probabilities etc. are initialized at start up. Data is read in from CSV files.

6. Input data: The model uses input data in the form of CSV files. Appendix F

[296] This can be changed and could be assigned individually to individual agents.

provides examples of these files.

7. Sub models: The model consists of a number of sub models as outlined below.

7.1Agent_Zero (AZ): The AZ framework [89] has been adapted to allow customers to keep track of emotions social interaction scores and incorporate logic associated with contract performance (see thesis section 6.4). The AZ framework is embedded in domestic customers and keeps track of emotions and provides a score which is used to assess relative aggregator performance.

7.2 Risk Evaluation: Agents calculate risk values by using an algorithm discussed in section 5.7 & 5.8 of the main part of the thesis.

7.3 Zip Trader: See section 6.2. Dave Cliffs ZIP trader [21] has been used to adjust bids during the simulation.

Appendix K: Notes for Long Term Cases presented in Table R-1 Appendix R

*Notes for Table R-1 in Appendix R.

<u>All cases</u> use the same_Customer and aggregator input data. All cases bar case 6 and 7 use equal number of bids in each bucket as the bucketing algorithm

<u>Base Case Assumptions</u>

Balancing demand sensitivity factor = 1.5. # *Balancing demand is 50% higher than those presented in the input file*

Generation output sensitivity factor = 0.3 # *All generators produce 30% of the levels specified in the input file*

Domestic Customer flexibility sensitivity factor= 1 # *Multiplies supply of flex volumes for each customer as contained in input file*

Domestic Customer bid price sensitivity factor= 1 # *Multiples Marginal costs in input file by said factor - used in customer bidding values*

Aggregator_opx_CPX_sensi_factor= 1 # *OPX CPX*

Elasticity long term effects flag on = True # *Yearly effect*

Elasticity short term effects flag on = True # *Elasticity short term i.e. monthly effects*

Probability of domestic customer agent receiving message = 0.3

Stimulation adjustment factor =1 # *e.g. need 1 stim from neighbour to get a 1 one stim score sent to agent zero V*

agentzero_learn_rate=0.1

agentzero_V_wt=0.333

agentzero_P_wt =0.333

agentzero_S_wt = 0.333

Aggregator number of buckets=10

Number of aggregators = 6

Bucketing algorithm - Equal numbers of bids in each buckets

Frequency adjuster for demand =1

Domestic customer yearly expectation =£10/Year

Aggregator Risk - as per data input (3 with risk hedging on and 3 aggregators with off)

Aggregator Numbers = 6

Domestic customers = 50000

Industrial Customers = 4500

Table K-1: Parameters – Base case

Appendix L: Stakeholder Equations for Cost Benefit Analysis

Equations for the different stakeholders under the base case. Figure L-1 provides a high level overview of how the three tables shown in more detail in Figures L-2 – L-4 are related. In particular Figure L-4 presents the difference between Figure L-2 and Figure L-3 and represents the net benefit to particular stakeholders. CPNew represents the clearing price with aggregation and CPbase without aggregation. A tax rate of 20% is assumed (0.2 factor in some equations). ISO's are assumed not to charge for their services. See section at end of tables for definitions of variables.

Clearing Price >>	CP base		CPNew		Benefits/Costs
Case >>	Base as Usual Case: No Aggregation		Flex Case		Difference
Aggregator	0		(CPNew *Vols_flex*marginagg - OPX-CPX)*.0.8		(CPNew *Vols_flex*marginagg - OPX-CPX)*.0.8
Customers providing flex	0		CPNew *Vols_dom_flex*(1-marginagg)		CPNew *Vols_dom_flex*(1-marginagg)
Energy Retailer	V_Dom_tot*margin_retail*CPbase*0.8/0.45*affectonDAprice factor		V_Dom_tot*margin_retail*CPNew*0.8/.45*affectonDAprice factor		-V_Dom_tot*margin_retail*(CPbase -CPNew)*0.8/.45*affectonDAprice factor
Domestic Customer energy Retail	-V_Dom_tot * ((1+margin_retail)*CPbase)/0.45*affectonDAprice factor	>>>>>>	-V_Dom_tot * ((1+margin_retail)*CPNew)/0.45*affectonDAprice factor	>>>>>>	(V_Dom_tot*(1+margin_reatil)*(CPbase-CPnew)/0.45*affectonDAprice factor
Government (Tax)	(Energy_Retailer +Producers_Generators_wholesale +ProducersFlex +Industrial_Customers_Wholesale)/0.8*0.2		(Aggregator+ Energy_Retailer +Producers_Generators_wholesale +ProducersFlex + Industrial_CustomersFlex + Industrial_Customers_Wholesale)/0.8*0.2		(Aggregator+ Energy_Retailer +Producers_Generators+Industrial_CustomersFlex + Industrial_Customers_Wholesale)/0.8*0.2
ISO	0		0		0
Producers Generators wholesale	margingen*CPbase*volgensbase*0.8*affectonDAprice factor		margingen*CPNew*0.8*vol gensnew*affectonDAprice factor		-margingen*(Cpbase*volgenbase-CPnew *volgennew)*0.8*affectonDAprice factor
Producers Flex	CPbase*volgenflex*0.8		CPNew*volgenflex*0.8		(CPNew-Cpbase)*volgenflex*0.8
Industrial Customers Flex	0		(1-marginagg)*CPNew*vol_ind_flex*0.8		(1-marginagg)*CPNew*vol_ind_flex*0.8
Industrial Customers Wholesale	(Industrial_out_val -vol_ind_tot*CPbase*affectonDAprice factor)*0.8		(Industrial_out_val -vol_ind_tot*CPNew*affectonDAprice factor)*0.8		-(Industrial_out_val -vol_ind_tot*(Cpbase-CPNew)*affectonDAprice factor)*0.8

Figure L-1: Cost /Benefit overview

See below for details on each of tables shown above.

CP price >> CP base

Case >> Base as Usual Case: No Aggregation

Aggregator	0
Customers providing flex	0
Energy Retailer	V_Dom_tot*margin_retail*CPbase*0.8/0.45*affectonDAprice factor
Domestic Customer energy Retail	-V_Dom_tot * ((1+margin_retail)*CPbase)/0.45*affectonDAprice factor
Government (Tax)	(Energy_Retailer +Producers_Generators_wholesale +ProducersFlex +Industrial_Customers_Wholesale)/0.8*0.2
ISO	0
Producers Generators wholesale	margingen*CPbase*volgensbase*0.8*affectonDAprice factor
Producers Flex	CPbase*volgenflex*0.8
Industrial Customers Flex	0
Industrial Customers Wholesale	(Industrial_out_val - vol_ind_tot*CPbase*affectonDAprice factor)*0.8

Figure L-2: Cost/benefits to stakeholders in Business as Usual case

CP price >> CPNew

Case >> Flex Case

Aggregator	(CPNew *Vols_flex*marginagg - OPX-CPX)*.0.8
Customers providing flex	CPNew *Vols_dom_flex*(1-marginagg)
Energy Retailer	V_Dom_tot*margin_retail*CPNew*0.8/.45*affectonDAprice factor
Domestic Customer energy Retail	-V_Dom_tot * ((1+margin_retail)*CPNew)/0.45*affectonDAprice factor
Government (Tax)	(Aggregator+ Energy_Retailer +Producers_Generators_wholesale +ProducersFlex + Industrial_CustomersFlex + Industrial_Customers_Wholesale)/0.8*0.2
ISO	0
Producers Generators wholesale	margingen*CPNew*0.8*vol gensnew*affectonDAprice factor
Producers Flex	CPNew*volgenflex*0.8
Industrial Customers Flex	(1-marginagg)*CPNew*vol_ind_flex*0.8
Industrial Customers Wholesale	(Industrial_out_val - vol_ind_tot*CPNew*affectonDAprice factor)*0.8

Figure L-3: Cost/benefits to stakeholders in aggregation case

Case >>	Benefits/Costs (Difference Case flex - BAU))
Aggregator	(CPNew *Vols_flex*marginagg - OPX-CPX)*.0.8
Customers providing flex	CPNew *Vols_dom_flex*(1-marginagg)
Energy Retailer	-V_Dom_tot*margin_retail*(CPbase - CPNew)*0.8/.45*affectonDAprice factor
Domestic Customer energy Retail	(V_Dom_tot*(1+margin_reatil)*(CPbase-CPnew)/0.45*affectonDAprice factor
Government (Tax)	(Aggregator+ Energy_Retailer +Producers_Generators+Industrial_CustomersFlex + Industrial_Customers_Wholesale)/0.8*0.2
ISO	0
Producers Generators wholesale	-margingen*(Cpbase*volgenbase-CPnew *volgennew)*0.8*affectonDAprice factor
Producers Flex	(CPNew-Cpbase)*volgenflex*0.8
Industrial Customers Flex	(1-marginagg)*CPNew*vol_ind_flex*0.8
Industrial Customers Wholesale	-(Industrial_out_val -vol_ind_tot*(Cpbase-CPNew)*affectonDAprice factor)*0.8

Figure L-4: Net (Differential) Cost/benefits to stakeholders

where:

CPbase	Clearing price before aggregation base case
CPNew	Clearing price average after introduction of aggregation
V_Dom_tot	Total domestic Volumes Mwh of customers in retail
margin_retail	Retailer margin
margingen	Generator owner margin
Volgensbase	Generator volumes Mwh before aggregation
Volgennew	Generator volumes Mwh after aggregation
Vols_flex	Volumume of flexibility supplied Mwh (Domestic and Industrial) = Vols_dom_flex+Vols_ind_flex
marginagg	Aggregrator margin. Customer receivers margin of (1-marginagg)
vol_ind_tot	Total Industrial customer volumes Mwh - All volumes incl flex
OPX/CPX	operating and Capital costs
Vols_dom_flex	Doemstic customers flex volumes
Vols_ind_flex	Industrial customers flex volumes
Industrial_out_val	Industrial company sales revenue
affectonDAprice factor	Assuming that proportion of the costs associetd with Balancing prices is apassed onto DA prices - reasonable assumption

Assumes

Vtot remains constant

Industrial margin is (1-marginagg) . In practice margins to the Industrial customer may be different from Domestic customers

Yearly Industrial volumes remains the same

45% of the retailer final price to consumers is associated with wholesale prices (CP)

Gens and Ind customers pay CP =- sop ignores some transmission and distribution costs

Value of Industrial output remains the same

That Generators pass on wholesale prices to their customers so their profits are a function of the wholesale price

Assuming that 5% of the CP proice in the balancing market is passed on to the Day ahead price - which would impact the retailing busininess

The equations have been used to create a net benefit analysis with graphs for various stakeholders under different assumptions shown in section 8.7 in the main thesis.

Appendix M: Updating Aggregator Bids

Although it would be possible to utilize a Learning Automata (LA) or Reinforcement Learning (RL) engine to estimate and change bids, an analyses of historical bidding prices with its effect of customer numbers would provide us with clues as to how to set the optimum value. Aggregators are collecting contract and bidding data and could analyse historical data on an ongoing basis to help set margins, fixed prices and more generally the hourly bids.

As margins to the aggregator increase, one would expect the number of customers to decrease as per Figure M-1a. Figure M-1 a & b assume a linear trend, but in practice other trends may be seen. In a similar way as the aggregator offers a greater fixed price to its customer's one would expect the number of customers to increase (Figure M-1b).

Use of Machine learning (ML) with such data, could also provide clues as to how the adjust the contract price (P_{fixed}) and or the margins, to maximize the profits to the aggregator.

Let us assume that the relationship between the number of customers can be represented as a linear relationship as per Figure M-1. In practice, points would not exactly lie on the line as shown.

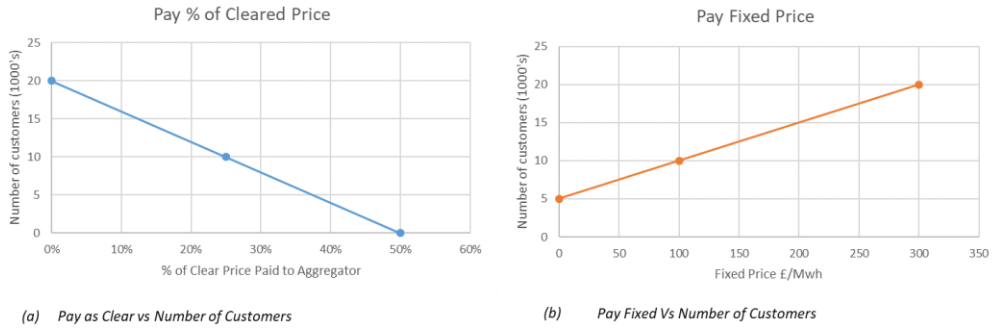


Figure M-1: Theoretical Relationship between number of customers and contract terms

In Figure M-1 a the number of customers would be expected to decrease as the aggregator increases the % of the profit (margin) that it keeps for itself. In Figure M-1 b an increase in the fixed prices offered to customers would result in an increase in customers.

With a linear relationship the profit π can be described by the following relationships, which changes as the number of customers, N, changes.

$$\text{Pay \% clearing price } \pi_{\%clear} = N * P_{clear} * \text{margin} * Vol_{mwh} \qquad \text{(M-1)}$$

$$\text{Pay Fixed Price } \pi_{fixedprice} = N * (P_{clear} - P_{fixedprice}) * Vol_{mwh} \qquad \text{(M-2)}$$

$$N_{\%clear} = m * \text{margin} + c \qquad \text{for \% clear model} \qquad \text{(M-3)}$$

$$N_{fixedprice} = m * P_{fixedprice} + c \qquad \text{for fixed price model} \qquad \text{(M-4)}$$

Where

N – Number of customers

P_{clear} - Expected clearing price in market £/MWh

margin - Aggregators margin %

$P_{fixedprice}$ - Fixed price offered £/MWh

Vol_{mwh} - Average volume of customers (MWh)

m - slope of relationship between number of customers and margin/fixed price

C – Intercept of linear relationship between numbers of customers and margin/fixed price

The slope of the line m and the intercept c can be estimated from the data presented in the form of (M-3) - (M-4). By substituting equation (M-3) into (M-1) and (M-4) into (M-2) we get (M-5) and (M-6). The profits with respect to N will be maximized when $\frac{d\pi}{dN} = 0$ (equations (M-7) and (M-8)).

$$\pi_{\%clear} = (m * margin + c) * P_{clear} * margin * Vol_{mwh} \qquad (M\text{-}5)$$
$$= (m * margin^2 + c * margin) * P_{clear} * Vol_{mwh}$$

$$\pi_{fixedprice} = (m * P_{fixedprice} + c) * (P_{clear} - P_{fixedprice}) * Vol_{mwh} \qquad (M\text{-}6)$$
$$= [(m * P_{clear} - c) * P_{fixedprice} - m * P_{fixedprice}{}^2)] * Vol_{mwh}$$

$$\frac{d\pi_{\%clear}}{dN} = 0 = (2 * m * margin_{opt} \;\; + c) * P_{clear} * Vol_{mwh} \qquad (M\text{-}7)$$
$$= (2 * m * margin_{opt}{}^2 + c)$$

$$\frac{d\pi_{fixedprice}}{dx} = 0 = (m * P_{clear} - c) - 2m * P_{fixedprice_{opt}}) \qquad (M\text{-}8)$$

Solving for $margin$ and $P_{fixedprice}$ provides the solutions shown in equations (M-9) and (M-10).

$$margin_{opt} = \frac{-c}{(2 * m * P_{clear})} \qquad (M\text{-}9)$$

$$P_{fixedprice_{opt}} = \frac{(m * P_{clear} - c)}{2m} = \frac{P_{clear}}{2} - \frac{c}{2m} \qquad (M\text{-}10)$$

The equations can be extended to include a quadratic representation or other types of trend-line. Use of such analysis after trend fitting data provides the aggregator with a mechanism to estimate the optimum margin or fixed price that it should offer. This is used in the Aggregator Agent logic.

Appendix N: Buckets - Limiting the Number of Bids

It will be difficult for the traditional operators of the power grid to interact with so many devices and individuals, so a "middle man", or a so called aggregator, will be required to manage their participation. The TSO and/or DSOs will still need to deal with a large number of aggregators, so to make the interactions manageable and to facilitate market clearing. The TSO/DSOs will need to limit the number of bids that each aggregator can submit to participate in Ancillary Services and/or flexibility markets. In California, Demand Side Response aggregators (DSR) are currently limited to a maximum of 10 bids per hour per aggregator [629]. The number chosen seems somewhat arbitrary, but fewer buckets would result in less granularity in price bids, whilst taking significantly more bid buckets would result in additional computational complexity and a requisite increase in solution time.

Aggregators will eventually take many forms and follow different types of business models. Some aggregators will specialize on different types of devices e.g. Electric Vehicles (EV) or CGCL. Some will focus on multiple groups. As a first step SmartNet developed five types of aggregators (Storage, CHP, CGCL, thermostatically controlled Loads [TCL] and Atomic Loads (e.g. washing machines) [165]). Each aggregator focuses on those specific devices only. The SmartNet aggregators do not have business models, model risk or have any form of learning. Aggregators do not compete against each other. One aggregator is placed at one MV/HV node. Aggregators take customer bids at marginal cost (MC) and bid at MC. This thesis extends the authors work on the SmartNet CGCL aggregator to include all of aspects like risk management, competition and representations of contracts.

So far the major focus of research has been on the aggregation of EV's, mainly from an algorithmic and optimization point of view [630, 631]. There is therefore a lack of work looking at aggregation of customers in general, as well as the role of the commercial aggregator. Optimization is one method that could be used to aggregate bids, but other alternatives should be investigated.

In that context, the work on bucketing that follows borrows from the finance and risk management sector as it is believed that many future commercial aggregators would use simpler more pragmatic solutions based on bucket concepts which fit well with portfolio and risk management theories and industrial practices.

Buckets could be time based [632], risk based [633], default based [634] or price /cost based.

Choosing which devices go into which buckets can be thought of as clustering exercise. At its simplest, if risk is ignored, bids can be clustered on price/cost but in practice, a more sophisticated clustering strategy would usually be required.

The current design of SmartNet does not address risk in any sophisticated way, but does include a cost adjustment, or delta, that can be added to the marginal bid cost. Calculation of the delta value has not currently been implemented.

Although simulation approaches using stochastic optimization with constrained chance [635] provides a potential solution to managing risk, the bucket approach presented in this thesis (Section 7.2.3) and used in the thesis simulation, will allow us to represent risk as in a way that is familiar to many risk professionals in trading companies and banks. In addition, run times for stochastic optimization algorithms can be of the order of 30 minutes to just over one hour [636] and may prove to be impractical in the context of real time electricity market clearing.

Appendix O: Estimates of Future Imbalance Volumes

O.1 The Impact of Drivers on Future Imbalance Volumes and its Volatility

Intra-day or balancing prices reflect the fact that forecasts or volume bids from the previous 24 hours have been incorrect or that system failures/ congestion issues have occurred that had not been foreseen.

However, there are a few papers that have looked at forecasting errors associated with wind power, EV charging and the effects of weather on demand. Nonetheless, the overall effect on imbalance volumes have not been addressed in literature.

In the section that follows a brief review of the effect of historical drivers on these various components is given along with a view on how different parameters such as wind penetration and EV penetration levels would be expected to change the volatility of balancing demand in the UK. Note this view does not include the impact of DSR. It therefor provides a view of imbalance volumes before DSR measures. This is useful as it means that this can be used as an input directly into a simulation without recourse to simulation of many networks. DSR effect measures are provided by the simulation.

O.2 Weather Impact: Forecasting 24 Hours Ahead

Imbalance volumes will be a function of system outages/congestion[297] issues and changes in weather forecast over the day. Outturn balancing or flexibility prices would

[297] Congestion is a sign of a constraint or set of constraints in a transmission or distribution system. Usually, physical flow restrictions are put in place by the operator to avoid system instability, overheating, and unacceptable voltage levels. Congestion may be permanent due to the network structure or may only be temporary due to an equipment fault.

be expected to be related to the effect on the underlying demand curve and the intersection of this adapted curve with the flexibility supply curve which in the future will include "supply" from EV's and flexibility provided by consumers.

Short-term weather forecasts are used extensively by the energy sector to improve forecasting of demand and renewable supply [637-640]. Indeed, being able to accurately forecast relevant meteorological conditions will become increasingly important for managing and mitigating stress in a future low carbon energy networks, and will be especially important for aggregation companies in forecasting prices and demand for their services.

Work on the effect of weather on electrical demand has been lacking either in scope or limited over the period in which it has been investigated [641] but the literature "focuses predominantly on winter-time peak demand conditions and a limited number of studies explore extreme stress using a whole system energy model "[642].

Peak electricity demand in the UK has a strong negative relationship with temperature where lower temperatures drive higher demand.

It is difficult to predict weather many days ahead but as time horizons shorten, forecast become more accurate. Figure 1 in reference [643] shows the accuracy of day ahead predictions of a site in Exeter and indicates that 1 day ahead temperature forecast could be +-0.5-0.75 degree C for this particular site at the 90% confidence level (reproduced in Figure O-1).

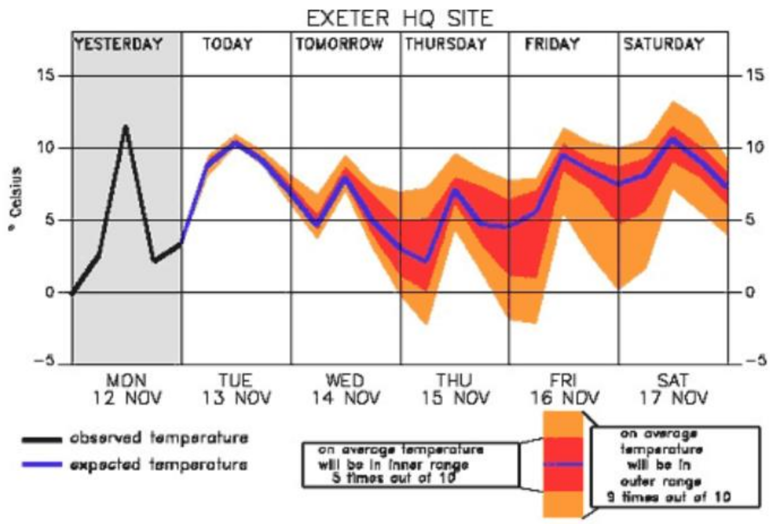


Figure O-1: Possible temperature values – with confidence levels (Figure 1 ref [643])

Thorton [644] indicates that a 1 degree C change in temperature equates to approximately 1% of the UK electricity demand. Drax [645] provides some figures in absolute terms which equates to around 1.3% [298].

Staffel uses his own model DESSTinEE (Demand for Energy Services, Supply and Transmission in EuropE)[299], a model of the European energy sector to 2050 to forecast demand and can be used to look at how temperature affects demand. Results presented in the paper [641] for the years 2015-2030, suggests that power demand sensitivity to temperature (GW per deg C) would be some 80-100% higher in the next 15 years. So one would expect demand flexibility to rise too[300]. See Figure 4 & 9 in [641] (Reproduced in Figure O-2 below).

[298] Thesis Author's calculation 820 MW/62 GW.

[299] https://wiki.openmod-initiative.org/index.php?title=DESSTinEE.

[300] Author's calculations based on data in Jan & Jul and using median temperatures and demand presented.

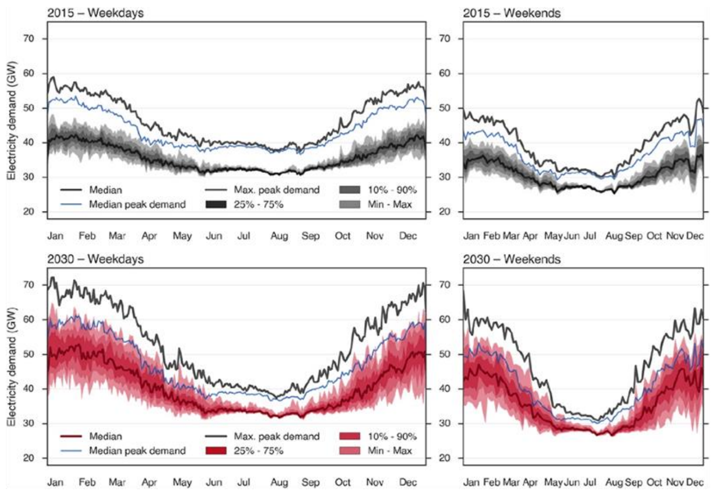
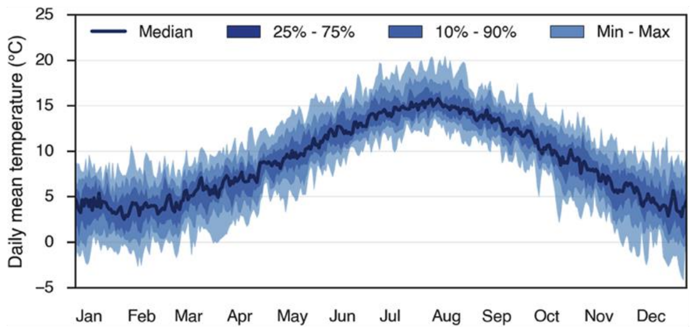


Fig. 9. The variability from year to year in gross electricity demand in 2015 (top) and 2030 (bottom) simulated across 25 weather years



Taken from I. Staffell and S. Pfenninger, "The increasing impact of weather on electricity supply and demand," *Energy,* vol. 145, pp. 65-78, 2018.

Fig. 4. Inter-annual variability of daily average British mainland temperature during 1991–2015.

Figure O-2: Demand forecasts (2015-2030). Taken from [641]

Note that it may be possible in future work to adapt DESSTinEE to provide better granularity on the potential for consumers to deliver flexibility. However, this only accounts for weather conditions, whereas much of the flexibility required will be due to local congestion on distribution networks.

Note that currently a 0.5 degree temperature change has approximately a 0.5% impact on UK demand forecasts a day ahead. This far lower than the numbers seen in [641].

O.3 The Impact of EV's, Wind and Solar on Imbalance Volumes

In the next few sections, literature is reviewed to estimate the various effects that EV charging, wind and solar forecasting have on day ahead demand forecasting and therefore its impact on overall imbalance volumes. Results from this literature review are used in a simple Monte-Carlo model to ascertain the impact on future balancing volumes under different scenarios of EV and renewable penetration.

O.3.1 Wind Forecasting

The penetration of wind in the UK is around 19%, with Solar at 6% [646]. In Scotland, however, renewables generated 42.9% of Scotland's electricity output in 2016 [647]. Balancing prices in 2015[301] were found to have an average volatility of 7% (SD) with a range of -15.4 to 11.2%. Wind Penetration levels were around 20% in the UK at that time.

Mechanisms such as EV's and the behaviour of customers in a potentially new flexibility market would have an effect on these balancing values. The work in [641] is UK wide, so specific areas in the UK could have much more volatile flexibility requirements, although this is a good starting point in which to test out potential impacts on the system. Work on congestion in the US North East market by FERC [648] shows that balancing volume requirements can increase by 50% during congestion periods in certain areas of the US . Note this was for transmission volumes only. Distribution congestion could be higher.

Graabak and Korpås [649] reviewed the variability of wind and solar resources in Europe (Sweden and Scotland) and reference a number of papers which have useful data for estimating variability on wind and solar resources. As renewable energy resources are likely to become more important in years to come, their impact on balancing volumes will become ever more important. The authors looked at various

[301] Authors calculations from data. Note volatility here refers to the standard deviation measure.

time horizons but the horizon of interest in this thesis is 24 hours. That is, what is the variability in forecasts over each hour of the next day. Weather is a major driver of the output of these systems.

Several of the papers reviewed in [649] refer to 'Step Changes' as a variability characteristic. Step changes are changes in resource availability that occur over short time steps ranging from minutes to a few hours.

Figure 4 in the reference shows examples of step changes in simulated power production scenarios in Scotland and Northern Sweden. In this example, production in Scotland decreases by about 40% (from 66% to 25%) over a 12-h period, while in Sweden it decreases from 38% to 10% in 18 h, followed by an immediate increases to 49% in 13 h.

O.3.2 Solar Forecasting Errors

Predicting solar output is more fraught with difficulties as cloud cover is obviously more difficult to predict day ahead.

Day ahead forecast errors for solar sites in South Korea in [650][302] are provided (see figure 7 in reference). With the authors new methodology errors in the range 3-5% are seen over the month but on certain days (figure 9); errors were much larger than this e.g. forecast 100% of output and got zero.

A study in the US South West [651] indicates that the forecasting techniques that they compared showed mean absolute errors in day ahead forecasting of 20% - 27% of the nameplate capacity (Table 2 in reference).

The point here is that systems with large amounts of renewable resources will

[302] See figure 7 in [650].

obviously produce greater uncertainty in the balancing market, and storage and DSR will help to relieve this.

In an Italian study [652], they show weekly numbers with errors ranging 2-5%. Fig 5 in the paper provides probability distribution for the day ahead forecast which suggests that forecast are within -10% and +15%

Table 8 in [649] summarizes 1 hour ramp rates from a study in [653] for differing amounts of wind and solar in the mix. If the distributions were normal this would suggest that variability over 24 hours could be of the order of 10-15% on average.

In a Swedish study [654] (also referenced in [649]) shows that a lower variation occurs for portfolios with more wind as a percentage when compared to solar. With 100% wind, output could be 20% out over 24 hours[303] but 100% with all solar.

O.3.3 EV Forecasts

Islam, Mithulananthan and Hung develop a probabilistic model for forecasting EV charging loads day ahead [655] and use a MATLAB model to forecast EV charging loads on a probabilistic basis. Visual inspection of Figure 13 in the reference shows that on a probabilistic basis, load forecasts may be some 10% higher than the maximum likelihood value expected from the methodology. Figure 16, which uses a machine learning approach in the same paper, suggest loads could be 16% lower than the expected (worst case with a confidence limit of 95%).

Xydas et al [656] use a support vector machine to forecast EV loads and compare various methodologies with actuals. Visual inspection of the figures in the paper (fig 5 and 6) indicates errors of 7-14% in forecasting EV loads a day ahead.

[303] Author estimate – based on square root of time and normal distribution.

Altogether, it appears that day ahead forecast errors of EV's could be some 16% in the worst case. Overall penetration of EV charging in the UK is expected to be around 30% in 2030 and 95 % by 2050[304] [70] .

O.3.4 Other Effects

UK penetration of wind currently sits at around 20%. From the discussion above, it would appear from that peak balancing demand would be expected to 10% of total demand if EV and solar penetration was assumed to be zero.

Assuming this was the case, then it is easy to deduce[305] that there is around 5% of imbalance volumes being produced by other effects i.e. generation outages, system failures and transmission constraints.

O.3.5 Combining the Forecasting Elements

Using literature, the previous section outlined the impact that various components could have on imbalance volumes expressed in percentage terms of total demand. A simulation which uses a simple Monte-Carlo model, which takes each of these errors into account and uses different wind and EV penetration values, has been made. When these components are combined, it would appear from the analysis below that balancing volumes over the next 24 hours could be as variable as 15-32% (peak), dependent on renewable energy mix and EV penetration levels. Figure O-(a) shows the worst case contribution for each element discussed above. This bar chart simply stacks the contributions without regard to any offsetting effects between the various elements.

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[304] Depending on scenario.

[305] By subtraction.

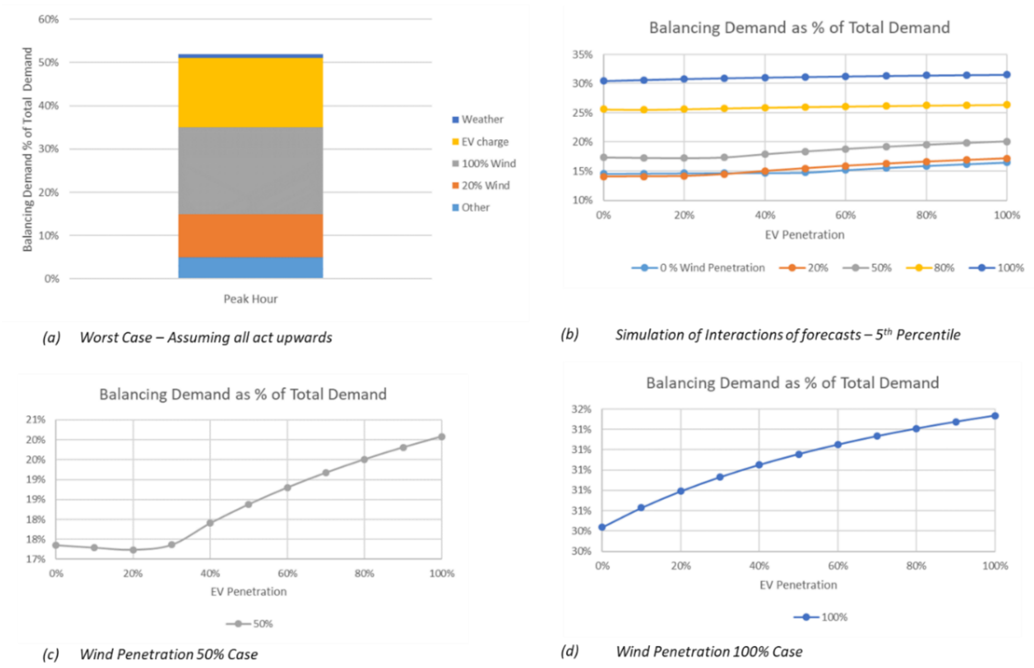


Figure O-3: Effect of various components on balancing demand

Figure O-3(b) shows the output from a Monte-Carlo simulation of imbalance volume changes for 5000 simulations. The P95[306] or a high balancing demand requirement is shown for a number of wind penetration cases. Variables in the simulation are as assumed normally distributed and independent. Independence results in a lower % balancing demand output than that shown by Figure O-3 (a) as when some components are high others are low and so on. This analysis is based on UK wide data so specific area or other operational issues could increase these values.

Assuming a normal distribution,[307] this equates to a standard deviation (SD) of around 7% to 10%. This about twice as high as the volatility derived in the time series analysis presented in section 2.6(Main thesis).

This simple analysis therefore suggests that balancing volumes could be some 50%

306 95th Percentile.

307 That ranges from +- 3 Standard Deviations.

- 100% higher in 2030, depending upon wind penetration and assuming a 30% EV penetration in 2030. Note a sensitivity factor that reflects this range has been used in the simulations presented in Chapter 8.

Appendix P: Generalized Logistic Equation Use

The generalized logistic function or Richards curve is an extension of the logistic or sigmoid functions originally developed for growth modelling. It allows for more flexible S-shaped curves such as those used in technology modelling. The function is named after F. J. Richards, who proposed the general form for the family of models in 1959 [657].

The Richards's curve has the following form:

$$Y(t) = A + \frac{K - A}{(C + Qe^{-Bt})^{1/\nu}}$$

where Y = weight, height, size etc., and t = time. It has five parameters:

- A: the lower (left) asymptote;
- K: the upper (right) asymptote when $C = 1$. If $A = 0$ and $C = 1$ then K is called the carrying capacity;
- B: the growth rate;
- $\nu > 0$: affects near which asymptote maximum growth occurs.
- Q: is related to the value $Y(0)$
- C: typically takes a value of 1. Otherwise, the upper asymptote is $A + \dfrac{K - A}{C^{1/\nu}}$

The shape of the curve can be altered with the appropriate selection of variables. The work herein use the symmetrical curve which takes values of A=0, K=1, C=1, Q=1, Beta =0.5 and V=1. However, experimentation with other potential curves was made. Note Q moves the symmetrical curve left to right, and increasing beta gets to the curve to the value of one earlier.

	Harsher than symmetrical	Symmetrical (Used in simulations)	Move to right	Easily pleased	One sided to the RHS	Nearly straight
A	0	0	0	0	0	0
K	1	1	1	1	1	1
C	1	1	1	1	1	0.5
Q	0.5	1	4	0.001	1	1
Beta	3	0.5	1	3	1	0.1
V	0.5	1	1	1	0.1	0.4

Table P-1: Suggested generalized logistic parameters for different curve shapes

To get the full extent of the shape of the curve, input values (x axis values) need to range from [-7,7] (see Figure P-1). The values in the simulation are [-1,1] so a transformation is used to fit the agent_zero scores which range from [-1,1] to the value of [-7,7] . In addition, the satisfaction score needs to range from [-1,1], so another transformation around the 0.5 is required.

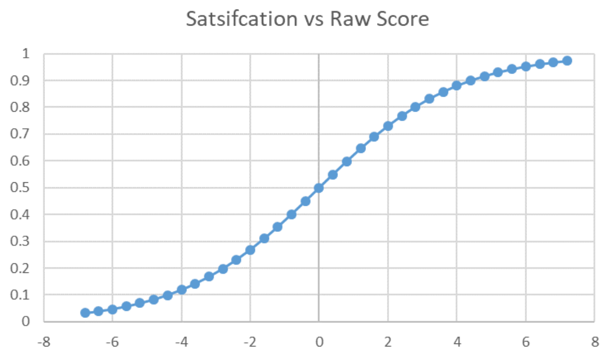


Figure P-1: Symmetrical general logistic curve

Domestic customer agents are given expected revenue targets as an input at initialization of the simulation. The concept modelled here, is that customers will be looking for an expected revenue. Amounts over this expected revenue will contribute to the normalized score. Based on internal discussion once the raw score is 1.5 times the expected revenue, the normalized score from the logistic equation would saturate at a value of one. See Figure P2 below.

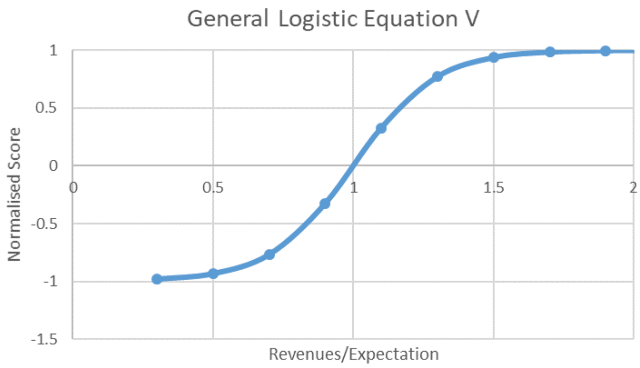


Figure P-2: Normalized score for Agent_Zero input

The curve in Figure P-2 has been coded into the domestic customer agent and is used to create a normalized score that can be used with the Agent_Zero framework.

Appendix Q: Valuation of an Aggregator Portfolio using a Call Option

The value of the aggregator portfolio can be represented using a call option. For completeness, the option valuation of aggregator bucket using a call option approach is shown in Figure Q-1. As discussed previously, Delta Hedging can be used with this option to manage risk using optimization techniques or by normal Delta hedging using futures (Ch 20 example in [256]).

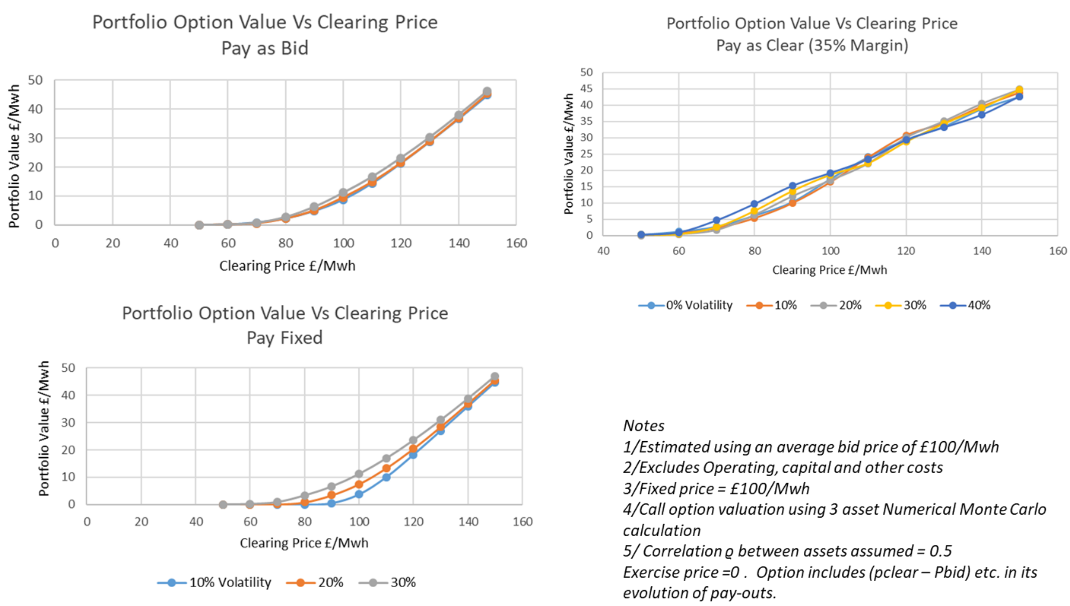


Figure Q-1: Aggregator call option value (£/MWh) for three business model cases

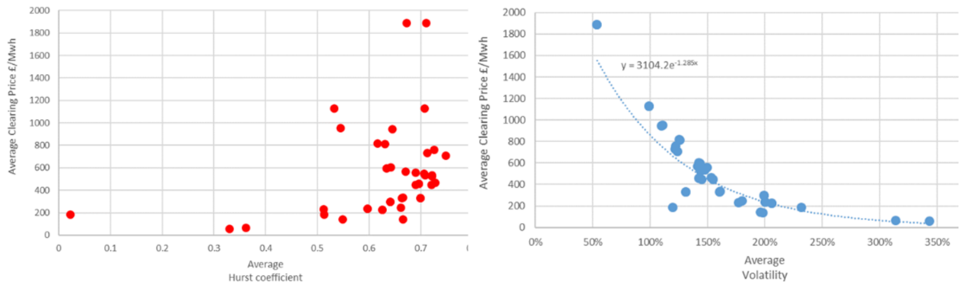
Appendix R: Longer Terms Simulations: Summary Results from 14 Cases

To show the effect of different assumptions on the longer-term evolution of the simulations, 14 cases are presented and summarized in Appendix K. In the future, an analysis using multilinear regression like that presented in section 8.2 (main thesis) will be used to investigate the impact of various drivers, but a simple comparison between the cases is performed here. Table R-1 below suggests that there is a relationship between clearing price and volatility in the said clearing[308], but at lower prices (e.g. less than £200/MWh) the relationship is less clear. There is less of a trend when CP is compared with the average Hurst coefficient.

Case Number	Brief Description	Assumptions/Parameters*	Average CP in year 5 £/Mwh	Average CP in year 1 £/Mwh	Average CP all years	Average Volatility in year 5 %	Average Volatility in year 1 %	Average Volatility all years %	Hurst Coefficient in year 5	Hurst Coefficient in year 1	Hurst Coefficient all years
1	Base Balancing Demand =1; OPX/CPX factor =0.4	Bal Demand Factor = 1, OPX/CPX factor =0.4, Yearly Elaticity = off	705	243	521	124%	180%	145%	0.75	0.66	0.72
2	Higher Balancing Demand; Higher customer expectations	Case 1 with higher Balancing Demand = 1.5 and customer expectation =£100/year	54	456	593	344%	143%	144%	0.33	0.70	0.63
3	Aggregator Risk Hedge On	As case 3 with all aggragtors with risk hedging On	62	457	600	314%	143%	143%	0.36	0.70	0.64
4	Aggregator Risk Hedge Off	As case 3 with all aggragtors with risk hedging Off	139	445	566	196%	145%	142%	0.55	0.69	0.67
5	Higher Balancing Demand and requires more stimulation from social interactyion to act	Bal Demand Factor = 1.7, Stimulation adjustment factor =5	1884	531	1127	54%	148%	99%	0.67	0.72	0.71
6	Astropy bucketing with Stimulation Factor of 5	Case 5 with Astropy Bucketing. Customer Expectations =£10/year Stimulation Factor =5	181	757	949	232%	123%	111%	0.02	0.73	0.54
7	Astropy bucketing with Stimulation Factor =1 . Different Fixed Price and Margin	Aggregators use Astropy bucketing algorithm to aggregate bids. Start FP=100 and initial aggragtor margin =0.3 , Stimulation adjustment factor =5; Balancing Demand Factor = 1.7; Stimulation Factor =1	228	727	944	177%	122%	110%	0.51	0.71	0.65
8	Customers use Marginal costs to bid No adjustmnet	As Case 3 but with with Domestic customer Expectations =£50/contract year; Start FP=100 and initial aggregator margin =0.3	233	223	294	200%	206%	199%	0.60	0.63	0.64
9	Customerts and Aggragtors both use Marginal costs to form bid	As Case 8 with Domestic customer Expectations =£50/contract year	233	223	294	200%	206%	199%	0.60	0.63	0.64
10	P=1; Logic preveails	Case3 assumptions but with balancing demand factor = 1.5 and P=1,V=0, S=0	1884	531	1127	54%	148%	99%	0.71	0.71	0.53
11	Domestic Customer follows Clear price rather than expectations	Domestic Customer Expectation = £10/yr, Balancing Demand =1.5	330	333	813	131%	161%	126%	0.70	0.67	0.62
12	Generation with Zip Trader rather than fixed Marginal Cost bidding	As Case x but Generators use a Clերaring Price following zip trader to alter bids.	137	446	547	199%	155%	148%	0.67	0.72	0.71
13	Domestic customer and Aggragator both follow CP rtaher set tragets in other ways	As Case 11 but with Aggregators and domestic customers following Clearing Price rather setting a target price based on expectations or profits	328	328	810	131%	161%	126%	0.70	0.66	0.63
14	V=1 Emotions prevail	As Case 10 but with P=0, V=1,S=0	181	462	553	120%	154%	1.498275	0.51	0.73	0.69

*Table R-1 Five-year long-term simulation case summary (*see notes appendix K)*

308 Note analysis based on averages and uses all years, the first year and last year data.



(a) Average Clearing Price Vs Average Hurst Coefficient *(b) Average Clearing Price Vs Average Volatility*

Figure R-1: Clearing price variability with Hurst coefficient and price volatility

Table R-1 also provides simulation summary values for average clearing price (CP), the volatility in those prices and Hurst Coefficients. Average CP's differ significantly from year 1 to year 5. This is not the case for case 8 and 9, where marginal costs are used to simulate clearing price output[309].

Rolling 24-hour clearing price averages are shown in figures that follow, to ease the understanding of trends[310]. Differences in evolution of the CP is seen across cases in Figure R-2.

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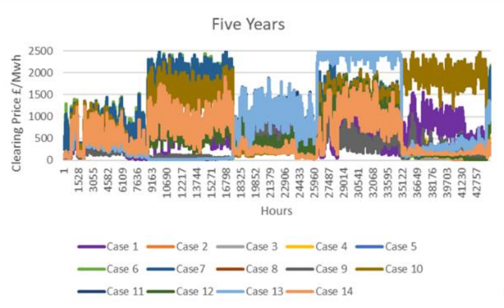
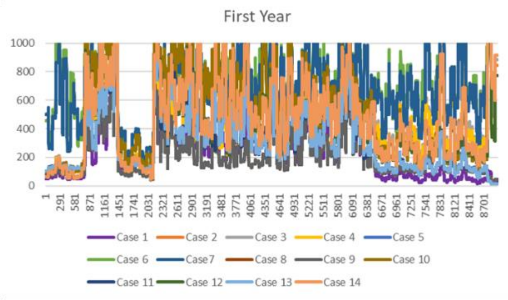
[309] This is the usual way to simulate clearing prices – e.g. as in SmartNet.

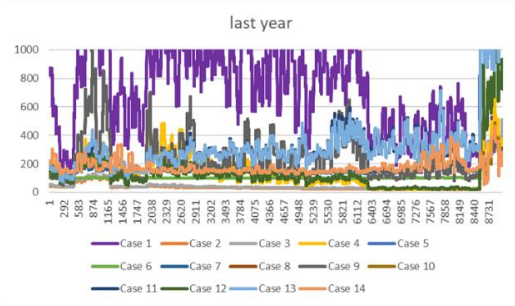
[310] Hourly graphs are too detailed to compare case trajectories.



(a) Clearing Price - 5 Year Evolution



(b) First Year Clearing Prices: Truncated at £1000/Mwh



(c) Last Years Clearing Prices: Truncated at £1000/Mwh

Figure R-2: Five-year evolution of clearing prices under different assumptions