Demand Side Self-Scheduling Under Dynamic Pricing Uncertainty

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This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Abstract

The ever increasing integration of renewable energy sources creates a challenge for electric network operation. Addressing the challenge called for changes in system operation, in particular at distribution level. Demand side flexibility is one of the key solutions proposed. Presently, customers start to actively manage their own energy consumption. To manage the growing demand side flexibility and utilise it to benefit grid operation, Demand Side Management (DSM) technologies are applied to manage the consumption, assist system balancing and ensure the security of supply. Direct Load Control (DLC) is a typical DSM technique, where demand corresponds to direct control signals and being directly controlled by an external entity with short notice. Under DLC, this may significantly discourage consumers to actively participate in DLC due to distrust and perceived intrusiveness.

This thesis proposes a novel customer-centred self-scheduling concept that is capable to overcome the distrust and perceived intrusiveness issues caused by DLC. The self-scheduling approach encourages consumers to participate and make their own decisions regarding when and how much they are going to consume domestic appliances rather than remotely switched by operators /aggregators.

Consumer-centred scheduling tools (a basic and a stochastic tool) have been developed in this research. The novelty of the developed scheduling tools is it minimizes the expense of end-users' energy consumption by automatically schedule load devices, while satisfies consumer's electricity usage preferences and their predetermined living patterns. Moreover, the novel stochastic scheduling tool also considered the rising uncertainty in the power system. It coordinates network/system operators' request and dynamic end-users energy usage behaviour, by combining long term and short term planning into one procedure.

The developed scheduling tools are able to aid consumers to monitor the electricity price signals intelligently, react to the network operators' requirements, achieve energy bill savings automatically, and satisfy consumers' energy consumption preferences at the same time.

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1. Xu, H., & Kockar, I. (2016, July). Participation of customers in Active Demand Side Participation programs under different pricing schemes. In *2016 IEEE Power and Energy Society General Meeting (PESGM)* (pp. 1-5). IEEE.

2. Xu, H., Kockar, I., Schnittger, S., & Rose, J. (2016, June). Influences of a hydrogen electrolyser demand on distrbuiton network under different operational constraints and electricity pricing scenarios. In *CIRED Workshop 2016* (pp. 1-4). IET.

3. Plećaš, M., Xu, H., & Kockar, I. (2017). Integration of energy storage to improve utilisation of distribution networks with active network management schemes. *CIRED-Open Access Proceedings Journal*, *2017*(1), 1845-1848.

4. Fan, F., Xu, H., & Kockar, I. (2019, June). Utilisation of energy storage to improve distributed generation connections and network operation on Shetland Islands. In *25th International Conference and Exhibition on Electricity Distribution*.

5. Kuusela, P., Koponen, P., Kockar, I., & Xu, H. (2019, June). An ICT cost comparison of different market structures for distributed ancillary services. In *25th International Conference and Exhibition on Electricity Distribution*.

6. Morch, A., Migliavacca, G., Kockar, I., Xu, H., Fernandez, J. M., & Gerard, H. (2019, June). Architectures for optimised interaction between TSOs and DSOs:

compliance with the present practice, regulation and roadmaps. In *25th International Conference and Exhibition on Electricity Distribution*.

7. Adams, S., Schnittger, S., Kockar, I., Kelly, N., Xu, H., Monari, F., & Bell, G. (2016). Impact of Electrolysers on the Network. Available at [Online]: https://www.ssen.co.uk/ImpactofElectrolysersontheDistributionNetwork/

8. Xu. H, Allan G., Fan F., & Kockar I. (2017). NINES 6A Commercial Arrangements and Economics Report. Available at [Online]: http://www.ninessmartgrid.co.uk/library/6a-nines-commercial-arrangements-and-economics-report/

   Fan F., Xu. H, Coote N., & Kockar I. (2017) NINES 2A Battery Operational Effectiveness Report. Available at [Online]: http://www.ninessmartgrid.co.uk/library/2a-nines-battery-report/

9. Bell G., Xu. H, Fan F., & Kockar I. (2017) NINES Project Knowledge and Learning Report. Available at [Online]: http://www.ninessmartgrid.co.uk/library/7a-nines-knowledge-and-learning-report/

Glossary of Abbreviations

ACF	Auto-Correlation Function
ADDRESS	Active Distribution network with full integration of Demand and distributed energy RESourceS
AI	Artificial Intelligence
AIC	Akaike Information Criterion
ANM	Active Network Management
ANN	Artificial Neural Network
AR	Auto Regressive
ARIMA	Integrated Auto-Regressive Moving-Average
ARMA	Auto-Regressive Moving-Average
BIC	Bayesian Information Criterion
BSP	Balancing Service Provider
CPP	Critical Peak Pricing
DDSM	Domestic Demand Side Management
DER	Distributed Energy Resource
DG	Distributed Generation
DLC	Direct Load Control
DNO	Distributed Network Operator
DSM	Demand Side Management
EBox	Energy Box
ESO	Electricity System Operator

EV	Electric Vehicle
FIT	Feed-In Tariff
G2V	Grid to Vehicle
GB	Great Britain
IC	Indirect Control
ICT	Information and Communication Technology
kW	KiloWatt
kWh	KiloWatt Hour
MA	Moving-Average
MAE	Mean Absolute Error
MLE	Maximum Likelihood Estimation
MW	Megawatt
NG	National Grid
NINES	Northern Isles New Energy Solutions
PACF	Partial Auto-Correlation Function
PV	PhotoVoltaic
RMSE	Root Mean Square Error
RTP	Real Time Price
SARIMA	Seasonal Integrated Auto-Regressive Moving-Average
SAVE	Solent Achieving Value from Efficiency
SSEN	Scottish and Southern Electricity Network
STOR	Short Term Operating Reserve
TINA	Technology Innovation Needs Assessment
TCL	Thermostatically Controlled Load
ToU	Time of Use

Nomenclature

i	Number of home appliances
s	Number of energy storage devices
ev	Number of Electric Vehicles (EVs)
sh	Number of storage heaters
pv	Number of PhotoVoltaic (PV) panels
t	A single time slot
T	Scheduling time horizon, currently is 24 hours
m	Number of time slot t covered under a single planning loop
τ	Time interval of rolling planning
N	Number of time interval
$\pi(t)$	Energy price at time t
$\pi_{FIT.gen}(t)$	'Generation tariff' of Feed-In Tariff at time t
$\pi_{FIT.exp}(t)$	'Exportation tariff' of Feed-In Tariff at time t
$\pi_{s.exp}(t)$	Exportation price for energy storage at time t
P_i	Power consumption of home appliance i
$P_{min}(t), P_{max}(t)$	Energy consumption limits at time t
$P(t)$	Energy consumption at time t

$u_i(t)$	Binary variable that indicate the status of a home appliance i at time t
$T_{i.\ ON}$	Continuous operating time of home appliance i since it has been turned on
$T_{i.\ OFF}$	Continuous OFF duration of home appliance i since it has been turned off
$T_{i.\ op}, T_{i.\ off}^{max}$	Limits of home appliance i's continuous operating and continuous off duration
$t_{ON.ini}$	Initial on/off time of home appliance i
$u_{i.ini}(t=0)$	Initial status of home appliance i
$U_{i\ ON}$	Total running duration of home appliance i
$U_{i\ ON}^{min}, U_{i\ ON}^{max}$	Limits of home appliance i's total running duration
$P_{s.\mathrm{pv}char}(t)$	Energy storage s charging power from PV at time t
$P_{s.\mathrm{exp}}(t)$	Energy storage s discharging/export power to grid at time t
$P_{s.char.grid}(t)$	Energy storage s charging power from grid at time t
$P_{s.dischar.app}(t)$	Energy storage s discharging power to supply home appliances at time t
$P_{s.dischar.ev}(t)$	Energy storage s discharging power to supply EV at time t
$P_{s.dischar.sh}(t)$	Energy storage s discharging power to supply storage heater at time t
$P_{s.char}^{min}(t), P_{s.char}^{max}(t)$	Energy storage s charging power limits at time t
$P_{s.dischar}^{min}(t), P_{s.dischar}^{max}(t)$	Energy storage s discharging power limits at time t
$u_{s.char}(t), u_{s.dischar}(t)$	Binary variables that indicate the charging/ discharging status of energy storage s at time t
$\mathrm{SOC}_s(t)$	Energy storage s State of Charge (SOC) at time t
$\mathrm{SOC}_s(t)^{min}, \mathrm{SOC}_s(t)^{max}$	Energy storage s SOC limits at time t
$P_{pv}(t)$	PV pv production at time t

$P_{pv.ds}(\mathrm{t})$	PV pv direct supplied energy to home appliances at time t
$P_{pv.exp}(\mathrm{t})$	PV pv exportation energy to grid at time t
$P_{pv.ev}(\mathrm{t})$	PV pv exportation energy to EV at time t
$P_{pv.sh}(\mathrm{t})$	PV pv exportation energy to storage heater at time t
$P_{pv}^{min}(t), P_{pv}^{max}(t)$	PV pv production limits at time t
$Percent.sun(t)$	Sun radiation (in percentage) at time t
$P_{ev.char.grid}(t)$	EV ev charging power from grid at time t
$u_{ev.char}(t)$	Binary variable that indicate the charging status of EV ev at time t
$P_{ev.char}^{min}(t), P_{ev.char}^{max}(t)$	EV ev charging power limits at time t
$\mathrm{SOC}_{ev}(t)$	EV ev SOC at time t
$SOC_{ev}(t)^{min}, SOC_{ev}(t)^{max}$	EV ev SOC limits at time t
$\mathrm{SOC}_{ev.target}$	EV ev SOC target at time $t_{ev.target}$
$t_{ev.target}$	EV ev target time for target SOC level
$t_{ev.return}$	EV ev return home time
$P_{sh.char.grid}(t)$	Storage heater sh charging (heating) power from grid at time t
$P_{sh.\mathrm{dischar}}(t)$	Storage heater sh discharging power (heat dispensing rate) at time t, if there is heat stored
$P_{sh.char}^{min}(t), P_{sh.char}^{max}(t)$	Storage heater sh charging power limits at time t
$u_{sh.char}(t)$	Binary variable that indicate the charging status of storage heater sh at time t
$\mathrm{SOC}_{sh}(t)$	Storage heater sh SOC at time t
$SOC_{sh}(t)^{min}, SOC_{sh}(t)^{max}$	Storage heater sh SOC limits at time t
$\mathrm{SOC}_{sh.target}$	Storage heater sh SOC target at time $t_{ev.target}$
$t_{sh.target}$	Storage heater sh target time for target SOC level

Chapter 1
Introduction

1.1. Introduction to the Research

The power system is undergoing fundamental changes nowadays. The drivers that cause the changes are numerous, including increasing penetration of intermittent renewable energy, growing production from distributed generation, rising number of electric vehicles on the road, and greater consumer awareness and participation etc. With such changes, network operation and planning are facing a growing uncertainty. Therefore, provision of flexibility that can coordinate the operation of diverse network components and functions must be organised.

The changes bring a greater emphasis on demand side flexibility, which will require active engagement with consumers. The way customers use energy is changing, and there are already customers actively improving energy efficiency, e.g. customers who have solar panels installed on their rooftops. However, the average peak and off-peak split for Economy 7 meters in 2017 in the UK, published by Ofgem [1], shows the average split is 58% and 42%, respectively. This indicates that i) customers who are actively responding to peak/off-peak energy price rates may not utilise the off-peak rates effectively, and/or ii) customers may not aware that they have Economy 7 tariff. From network operation point of view, by properly utilising distributed flexibility resources, it can benefit the network with alleviating network constraints and therefore deferral of network reinforcement. As a result, it is necessary to apply Demand Side Management (DSM) technology so to benefit customers and assist them actively responding to energy tariffs, and also to provide increased demand side flexibility for network operation.

DSM covers a broad range of techniques [2-4], which typically refers to the methods applied to manage the consumer side by network/system operators. The load consumption can be managed through peak reduction and/or load shifting, in order to keep the energy system balance and security of supply. There are pilot projects across the world that have been engaging with demand side customers to trial operational flexibility, which can be provided from industrial consumption activities and residential home devices.

Direct Load Control (DLC) technique [5, 6] is one of the typical DSM techniques applied to the consumer side, where demand e.g. home appliances, are reacting to direct remote control signals sent by network/system operators or on changes in system wide parameters such as system frequency, typically with relatively short notice. Under current pilot schemes, DLC is trialled on specially equipped home appliances which are frequency responsive, e.g. refrigerators and air conditioners. However, the implementation of DLC may discourage consumers to actively take part in the DLC program due to perceived intrusiveness.

In order to overcome such perceived intrusiveness, DSM methods based on Indirect Control (IC) [7] where customers receive external signals (incentives) to which they may or may not respond have started to emerge. The external signals can be energy prices, e.g. Economy 7 tariff is one of the most common used Time of Use (ToU) pricing tariff in the UK. In addition to Economy 7, varying energy tariffs are starting to appear in the UK. The Financial Times reported that households in the UK have been offered Britain’s first “time of day” electricity tariff with varying prices between periods of high and low demand in 2017, which are supplied by Green Energy UK [8]. Real–Time Pricing (RTP), as another kind of energy tariff with dynamic rates, can also be offered to the demand side. The price rates of RTP vary throughout the day based on the outcomes of market clearing. Considering the dynamic demand side responses that correspond to price signals under the IC, it is necessary to capture the dynamic responses and enable the utilisation of active customer participation for network operation. Coordination between network operators/aggregators and active end-users is therefore required.

By considering these elements, the thesis will show the developed customer centred self-scheduling tools are able to help consumers to monitor the electricity price signals intelligently, react to the network operators' requirements and achieve energy bill savings automatically, in the condition of satisfying consumers' energy consumption preferences.

1.2. Justification for Research

The European Commission proposed the Clean Energy for All Europeans Package (also known as the Winter Package) on 30 November 2016 [9]. In the Clean Energy for All Europeans Package, it is proposed to be a customer centred clean energy transition, which will give consumers more controllability on their own energy consumption, energy choices and energy costs, through deploying smart metres and market-based electricity pricing [10]. Also, the Department for Business, Energy & Industrial Strategy suggests in [11] to facilitate more engaged and more active demand side in the future. Opportunities and benefits of DSM application have been summarised in this thesis based on [12]. The DSM application can delay network reinforcement, balance system supply and demand, and alleviate network constraints, etc. Moreover, in the UK balancing market operated and managed by National Grid (NG) ESO (Electricity System Operator), NG ESO has outlined a number of services that large scale and/or aggregated demand side customers can participate [13]. Electric Vehicles (EVs), energy storage devices and solar panels can also be considered and controlled in DSM programs, to provide additional load flexibility and to improve utilisation of renewable energy.

The overall objective of this research is to develop intelligent scheduling tools that could be applied to individual households and better position customers when they are facing uncertain electricity prices, in the condition of satisfying customer's energy usage preferences first. The scheduling tools also facilitate coordination between customers' responses and network operators' request, so to benefit network operation.

Emerging of smart technologies, such as smart meters and smart home appliances, makes it possible for decentralized residential DSM [14, 15]. Customers are able to switch on and off their smart appliances through using a smartphone app, such as the HIVE app [14] innovated by British Gas. RSE has also developed and tested a prototype customer-engaging system [16], which can notify demand scheduling suggestions to customers and check if the suggestions have been accepted. Using HIVE and similar systems can be seen as the first step towards active consumer engagement. A major problem of such systems is customers need time to learn to use them [17]. Therefore, there is a need for customers to be able to manage their consumption in an intelligent and automatic way, so that the home appliances are able to do self-scheduling based on customers' preferences.

This research proposes a self-scheduling concept that considers consumers' energy usage preferences. Social aspects are investigated to discover underlying consumers' behavioural patterns and preferences. The preferences will then be taken into consideration in the scheduling tools (a basic scheduling tool and a stochastic tool) developed in this thesis, and allow customisation of customer electricity demand. The approach helps customers to decide how to schedule various appliances within the household, when the customers are facing an increasing diversity of energy pricing tariffs. Self-scheduling of demand side is applied to micro-grid with combined heat power, energy storages, and Demand Side Responses (DSR) in [18] to reduce daily grid operational cost. It is also used by industrial customers to optimise their load profile so to provide flexibility to the power system [19] and to minimise the customers' energy procurement cost [20]. In addition, self-scheduling of home appliances to be shifted among different energy carriers (gas, heat and electricity) is presented in [21]. Instead, the research developed a basic customer-centred self-scheduling tool, which focuses on self-scheduling of home devices, energy storages, EVs and solar panels to minimise customer's energy bill payment and also maintain customers' comfort level.

Different home energy management schemes are reviewed in [22], using various pricing strategies and optimisation techniques. Economic incentives are regarded as the most effective way of engaging with customers. Thus, in this thesis, different pricing strategies are tested in the basic scheduling tool, including ToU pricing and RTP. Economy 7, as the most common ToU pricing tariff in the UK, has been tested in the tool. Moreover, with the UK energy system evolving, [11] sees that new ICT (Information and Communication Technology) will make new forms of demand side participation possible, e.g. RTP. Thus, in addition to the ToU pricing (Economy 7 tariff), RTP is also tested in the scheduling tool developed in this research. Considering the stochastic nature of RTP, it is essential to forecast future RTP rates, so to help consumers better responding to dynamic price rates when scheduling the home appliances. In this thesis, future RTP rates are forecasted using Auto Regressive Moving Average (ARMA) time series model, based on historical PJM price data. Furthermore, scenario trees of future RTP rates are built by means of scenario generation and reduction algorithms, so to characterise and represent the continuous random rates of RTP.

In addition to self-scheduling, the research also enhances the scheduling tool with the ability to coordinate network operation and demand side flexibility, by considering the following aspects of dynamic electricity demand: i) energy usage behavioural change of customers caused by stochastic prices, and ii) customers adaption to the state of the network into which this active participation is integrated. In order to capture these dynamic aspects and allow for the integration of active customer participation, a stochastic self-scheduling tool is built in this thesis, by enhancing the basic tool, which is able to incorporate demand flexibility at the user level for network operation. The stochastic tool considers rolling optimisation, and rolling planning [23] technique is applied. The stochastic tool therefore schedules consumers' consumption on a rolling basis. A home energy management system is proposed in [24] to minimise consumers' energy bill costs based on real time signals. It also recognises the importance of rolling operation to follow the changes in the price signal throughout the day. This research further improves the rolling planning techniques by employing two-stage RTP scenario trees that represent the stochastic RTP rates and involving external notifications from network operator/aggregator side. If an external notification is received, such a signal will be incorporated into the stochastic self-scheduling tool. As a result, customers will be able to adapt to dynamic network status and respond to inflow stochastic prices automatically.

To summarise, recent research on dynamic demand responses carried out in [25-28] focus on the control of demand responses and managing the demand response to achieve peak reduction, stable power system frequency, and security of supply. Differently, this research considers the consumer preferences of energy usage, and the scheduling tools developed allows the actively participated end-users to take control of their home appliances and all of the decisions are made so to achieve objectives of customers. It encourages consumers to participate and make their own decisions regarding when and how much they are going to consume. Both the basic and stochastic tool minimize the expense of end-users' energy consumption while satisfying consumer's electricity usage preferences and their predetermined living patterns. Moreover, the stochastic tool links demand side flexibility with network operation requests.

The novel aspects of the reported research can be summarised as follows:

- An investigation of methods suitable for DSM application to residential consumers, including control-based and market-based approach. The development of a suitable framework for active participation customers using novel customer-centred self-scheduling concept that allows consumers' energy usage preferences being considered,
- The development and implementation of a basic customer centred self-scheduling tool that is able to control modelled devices (including home appliances, energy storage, EV, storage heater and solar panels) based on various electricity price tariffs. The price tariffs tested are ToU pricing (ToU and Feed-in Tariff (FiT) for houses with solar panels) and RTP,
- A study of approaches suitable for forecasting future RTP, including time series model forecasting and scenario tree construction. An implementation

of two-stage RTP scenario trees, by means of steps comprising scenario generation, scenario reduction, and scenario tree evaluations,

- An implementation of a novel enhanced stochastic scheduling technology that combines the developed RTP scenario trees and rolling planning technique with the basic scheduling tool. The stochastic scheduling tool allows active customers to respond to the rising uncertainty from the power system (reflected by dynamic pricing signal), and assist network operation through external notifications sent by operators/aggregators, while respecting end-users' behavioural preferences,
- A comparison between the basic scheduling tool and the stochastic scheduling tool.

1.3. Thesis Overview

This thesis is organised as follows. It starts with a background review of the network needs nowadays in Chapter 2. Opportunities and benefits of DSM are summarised at different network layers. A variety of DSM approaches are investigated, which are categorised into two groups, including control-based and market-based approaches. To apply DSM to customers, smart meters are required as they enable the two-way communication between the grid and customers. DSM pilot projects that employ DSM in the US, the EU, and the UK are discussed with the presentation of results of the DSM trials in Appendix I.

At the beginning of Chapter 3, a discussion on DLC and customer-centred approach is made and it is decided that the research will use the customer-centred approach with price incentives. In order to carry out the bottom-up customer-centred approach, it relies on customers to take control of their home appliances. Since the control of home appliances is not an easy task, especially when the customers are facing with dynamic pricing rates. A customer-centred self-scheduling tool that enables actively participate customer to automatically respond to price signals is developed. Typical energy consumption preferences of customers are investigated based on social survey results. In addition, the scheduling flexibility levels of different home appliances are discussed. Case studies of the developed customer-centred scheduling tool are carried out in seven virtual household models with ToU pricing. Home appliances (selected from different scheduling flexibility levels), energy storage, electric vehicle, storage heater and PV panels are considered in the virtual household models. For the house with solar panels, FiT is also applied. Mathematical formulation of the customer-centred scheduling tool in these household models are given in Chapter 3. The objective of the tool is to minimise the customers' energy bill payment. All the case studies have sufficient evidence showing the basic customer-centred scheduling tool succeeded in achieving minimal energy payment.

Stochastic RTP is also trialled into the basic customer-centred scheduling tool. The potential future scenarios of RTP are tested in the basic tool in Chapter 4. ARMA time series model is selected as the forecasting method for future RTP rates, after briefly reviewing the major forecasting approaches. The Box-Jenkins methodology is applied for fitting an ARMA model into the historical RTP data from PJM. An ARMA (4, 4) model is fitted by means of model identification, model parameters estimation, model diagnostics, and information criterion selection steps.

The RTP scenario tree is established through three steps in Chapter 5, which are scenario generation, scenario reduction, and scenario trees evaluation. By applying a scenario tree, the stochastic RTP rates are revealed gradually with the process of moving to the next stage. The composition, including the nodes and paths, of a multi-stage scenario tree is reviewed in this chapter. Furthermore, typical scenario generation and reduction approaches are investigated as well. One thousand scenarios are generated through sampling the error term in the ARMA (4, 4) time series model. Different scenario reduction algorithms are applied to downsize the generated one thousand scenarios. The reduction techniques are Kantorovich forward selection method based on probability distances, K-Means centroids algorithm and K-Means 'local' and 'global' maximal average distances algorithm based on clustering. Last step of building RTP scenario trees is to evaluate the quality of the trees acquired from different scenario reduction algorithms. Stability of the trees is tested. Based on the test results, Kantorovich forward selection algorithm is used for establishing the two-stage RTP scenario trees.

The established two-stage RTP scenario tree is integrated with rolling planning technique in the stochastic customer-centred scheduling tool in Chapter 6. The stochastic scheduling tool is developed to help customers to adapt to the increasing dynamics in the power system. The rolling planning technique is introduced, and the application of rolling planning in the research is further improved by including two-stage RTP scenario trees and external notifications in the planning. At the start of each planning loop, an RTP scenario tree is built based on the past price data. The scenario with the highest probability of occurrence will be selected by default to be applied to the household. However, if there is any external notification on the change of price signals from network operator/aggregators, the external notification will be employed into the household. The combination of the rolling planning technique and the two-stage RTP scenario tree provides adequate information for scheduling the household at each planning loop. Case studies of the stochastic scheduling tool with different external notifications in different household models are shown in Chapter 6. The results of the case studies illustrate that the stochastic tool is able to help customers to be more flexible when facing volatile dynamic prices. In this way, the stochastic tool allows customers to pay less when compared to the results of the basic tool. Therefore, by coordinating active participation households with network (system) operators/aggregators and updating price rates in each rolling time interval, active-participated consumers can achieve energy bill savings and help to react to certain network problems (through the price signals).

Chapter 2
Demand Side Management in Smart Grid

2.1. Smart Grid

The present electric grid is facing tremendous challenges. The UK aims to achieve zero greenhouse emission by 2050. Challenges arise with increasing load demand, limited network capacity ageing infrastructures, considering a growing penetration of renewable and low-carbon energy, and electrification of heat and transportation. Ofgem published its decarbonisation plan [29] in February 2020, which sets out the actions for the next 18 months. The plan aims to develop a cost-effective smart grid that can integrate the varying factors in order to maintain a secure and stable supply, but also to achieve a more flexible operation.

"Smart Grid" was an idea raised as an electricity grid solution in the 21st century. It involves revolutionary changes, such as the way of generation (e.g. penetration of renewable energy resources) and the way of demand consumption (e.g. demand side engagement and smart homes). An overview of the smart grid is given in Figure 2-1 [30], this includes i) complexity and uncertainty of energy supply, due to integration with renewable resources and distributed generations; ii) utilisation of (distributed) energy storages, e.g. electric vehicles; iii) intelligence of active consumer engagement and responses; iv) new information and communication structure, e.g. smart metering for demand participation and smart homes; v) decentralised power system control architecture with distributed operation centres.

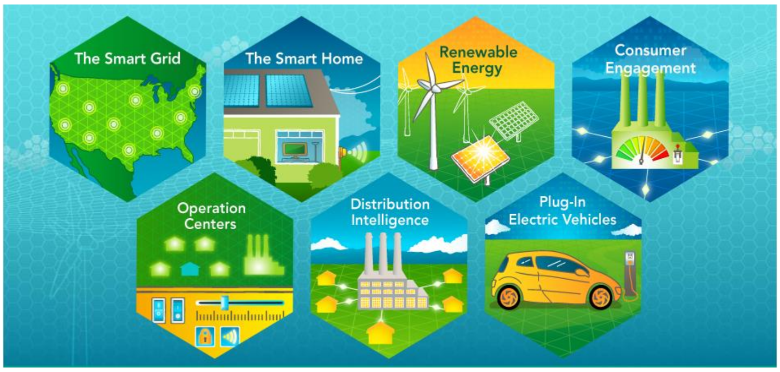


Figure 2-1 What is the Smart Grid? [30]

The Smart Grid Forum's vision for a Great Britain (GB) smart grid is [31]:

"A smart electricity grid that develops to support an efficient, timely transition to a low carbon economy to help the UK meet its carbon reduction targets, ensure energy security and wider energy goals while minimising costs to consumers. In modernising our energy system, the smart grid will underpin flexible, efficient networks and create jobs, innovation and growth to 2020 and beyond. It will empower and incentivise consumers to manage their demand, adopt new technologies and minimise costs to their benefit and that of the electricity system as a whole."

The GB smart grid aims to replace the conventional fossil fuel electricity production with renewable energy resources, to enable power system operational flexibility, to integrate and operate with Distributed Energy Resources (DERs), and to enhance electricity system reliability. The installed renewable capacity in the UK is presented in *Figure 2-2* [32]. With the increasing capacity, it can be observed the majority comes from wind and solar PhotoVoltaic(PV). The UK has become the most dynamic PV market in Europe [33]. A detailed concept of GB smart grid is presented and discussed in [34]. With the requirements for intelligent, automatic and flexible decision making, one of the ways to improve system flexibility is to apply DSM techniques, in order to achieve a more manageable, smarter electric power system. Active demand can be responsive to external signals, such as energy price signals and device control signals (i.e. load shedding/load shifting signals) etc. [35-37].

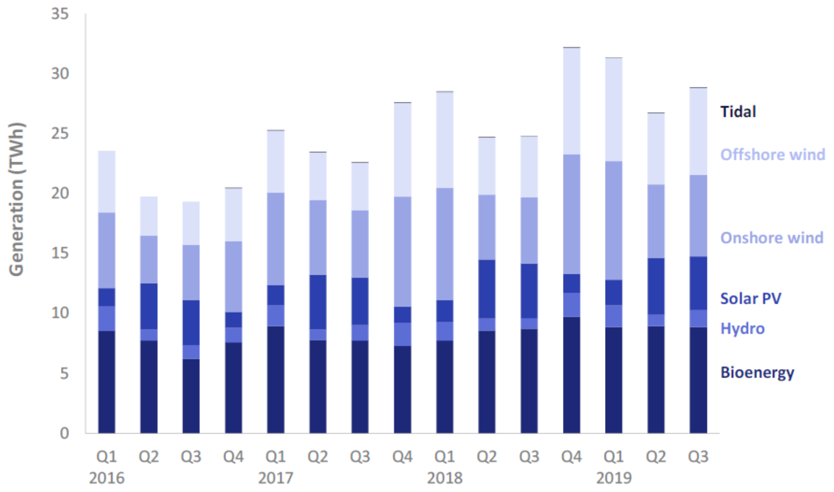


Figure 2-2 Installed Renewable Capacity in the UK from 2016 to 2019 [32]

2.2. Demand Side Management

2.2.1. Introduction

Demand Side Management (DSM) plays a vital role in the grid revolution, as it helps to ensure a sustainable and reliable network supply. It covers a wide range of techniques and methods associated with managing electricity consumption. DSM is not a new term and it normally refers to intelligent energy use techniques applied to the demand side, in order to i) improve energy efficiency, assist network operation (e.g. utilise renewable energy) and lower carbon emissions; and ii) achieve cheaper electricity bills for customers. According to [38], Demand Side Management is *"a mechanism through which the load of some customers is managed (i.e., reduced or shifted to a different time period) in response to certain conditions (e.g., price, network constraints, emergencies, etc.)."* It enables industrial, commercial and residential consumers to alter and/or shift demand so to benefit network operation. Customers therefore could draw or use energy from the grid at specific times, e.g. when there is surplus renewable energy. Residential customers will expect to be rewarded (either by incentives or by reduced bill payments) if they are available for DSM in the form of altered demand profile. Industrial and commercial customers may change business operating patterns by performing certain tasks at times when energy prices are low, and they may see a drop in energy use costs.

When the peak of the electric demand is higher than the supply, raising the generation level to meet the maximum point of the load peak can solve this problem. However, this traditional way might not be suitable for the future smart grid. This is because conventional generators have start-up and cooling-down time and associated cost to reach the supply amount targets [39]. Since the generation should match the maximum amount of demand, it will lead to an earlier start and longer running time for the machines. As a result of that, a relatively large amount of energy is wasted. Moreover, considering the integration of renewable energy which is clean to use and abundant in the UK, intermittent renewable energy cannot be controlled to meet peak demand at specific time periods.

To keep the maximum consumption in acceptable limits and also to improve the utilisation of renewable energy, DSM could use peak shaving to reduce peak energy use, load shifting to fill in troughs, as given in Figure 2-3 [35]. Peak shaving cuts the over-limit amount during the peak time periods. Load shifting is a flexible approach and the amount exceeding the allowance is re-distributed to trough time periods. Energy efficiency is improved through the permanent replacement of appliances with higher efficiency or additional insulation. By improving energy efficiency, reduction in energy consumption and long-lasting energy savings can be achieved. These approaches could be combined and the combination would be more flexible and acceptable for the demand side. However, it should be noted that when applying load shifting, this may cause another peak demand if consumption is shifted towards the same time period. Proper designs of control/price signals would be required when applying DSM techniques.

2.2.2. DSM Opportunities and Benefits in the UK

Moving to an autonomic, intelligent and low-carbon electric power system, many opportunities exist for potential DSM application considering the benefits that DSM could bring to the GB network. The DSM opportunities considered in Figure 2-4 [12] involves four network layers, which are generation, network, supply and consumer levels. Benefits therefore are discussed based on opportunities for these four layers.

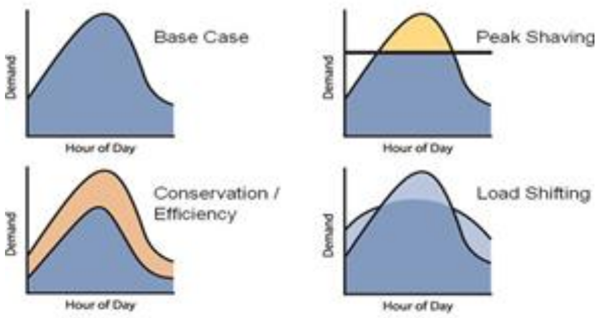


Figure 2-3 DSM Objectives [35]

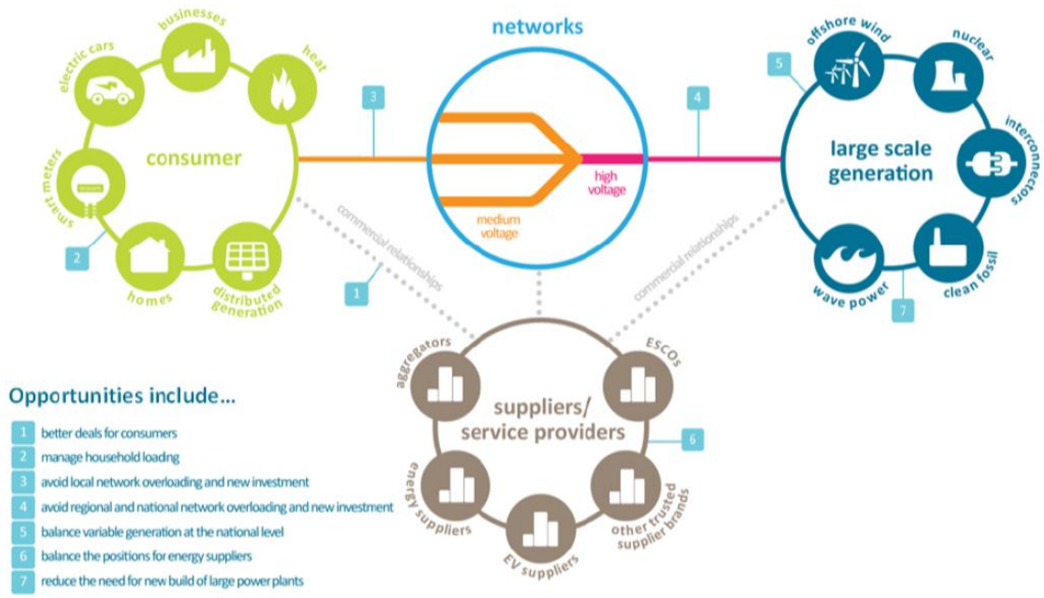


Figure 2-4 DSM Opportunities [12]

2.2.2.1. Generation Layer

In order to match the supply and consumption at any time during daily network operation, the amount of generation must be able to meet the maximum demand. This is especially problematic during peak times as some generators need to spin up and cool off for a period of time, only to meet the peak demand. This is because the result of not matching supply and demand is severe and will immediately cause chain reactions in the power system, leading to potential blackouts. As a result, the system operator must ensure it has adequate generating capacity head/foot room. According to [40], the average utilisation of generation capacity in one year compared to the given average load demand is below 55%, which is not ideal. This issue will be exacerbated with the integration of more intermittent and variable renewable energy sources.

This gives a great opportunity for DSM as it provides flexibility into the power network through smoothing the peak and filling troughs. Thus, it can decrease the additional generation capacity that is used for matching the peak demand. Moreover, DSM has the potential to provide balancing services which in turn can keep the power system stable and reliable from blackouts, generator breakdowns and interruptions. National Grid (NG) Electricity System Operator (ESO) has considered a list of services that DSM could provide/participate in the UK balancing market [13], the services are discussed in detail in the section 2.2.3.2. In addition, DSM could be applied to integrate renewable energy by shifting the demand to match varying renewable generation. In this way, network balance could be maintained while at the same time utilisation of renewable sources is higher. DSM therefore could achieve better utilisation of generation production.

2.2.2.2. Network Layer

The transmission and distribution network is designed to transport energy from where it is generated to where it is consumed. The capacity of transmission and distribution networks is rated to satisfy the highest demand, which occurs at a single period during the year. In the UK, there is a significant amount of wind resources situated in the north (Scotland). However, the majority of the demand is in the south. As a result, Scotland exported 29% of its generated electricity, to other places in the UK, with virtually all of these net exports going to England [41]. Considering the transmission and distribution network usage costs and potential congestions might occur in the network for such a long distance, the generation in the south part with a higher cost is used to supply the demand instead of using that from the north with lower generation cost. This leads to a higher cost for network operation [40]. Moreover, since an increasing number of Distributed Generations (DGs) are connecting into the grid nowadays, proper management and operation of the DGs in the distributed network is an issue for both Distributed Network Operators (DNOs) and transmission network operators.

With the increasing demand and generation, the ageing GB network is approaching its capacity limitations and requires reinforcement. The expenses of replacing lines/cables and transformers are high. If DSM is rolled out at a local level, it could benefit the network to digest the generation and demand locally, which will help to defer the network reinforcement. Moreover, DSM could enable DGs to be connected to the present distribution network and also improve utilisation of DGs [42]. If DSM scheme is rolled out at a national level, system operator could coordinate aggregated demand responses to solve network imbalances and congestions. As a result, the reduction and shift of load consumption could benefit the network with fewer congestions.

2.2.2.3. Supply Layer

The energy suppliers have commercial arrangements agreed with generator companies and they offer a variety of tariffs to customers. As DSM could contribute to maintaining network balance, it can bring benefits to suppliers to operate more efficiently as an imbalance between supply and demand could result in a high payment from suppliers. Therefore, DSM helps energy suppliers to stay competitive on their retail pricing [12].

2.2.2.4. Demand Layer

The minimum peak occurred during summer nights is only about 30% of the winter peak [40]. DSM focuses on the consumer side and it applies DSM techniques in order to shape the demand curve, so that the reshaped curve could benefit the network and consumers themselves. Customers can switch suppliers from one to another and choose cheaper tariff. As suppliers offer competitive rates to their customer through more efficient network operation enabled by DSM, customers could benefit from better supply deals. Moreover, tailored incentives could be offered to the customers, in order to facilitate active demand responses. The incentives could be payments that are made at the beginning to attract customers to join the DSM, or discounted tariff rates at certain time periods, or simply a greater awareness of sustainable and low carbon future. For example, fuel poverty customers can participate in DSM to save their energy costs, and customers who have Electric Vehicles (EVs) can save their spending on the charging activities if they allow their EVs to be charged during time periods of discounted rates. In addition, customers could also manage their home appliances' consumption by themselves if they are willing to. In this way, they could maintain their comfort level and participate in DSM at the same time.

2.2.3. DSM Programmes

Demand side management techniques are the methods applied to network customers, including business and residential customers, so to contribute to DSM objectives and benefit network operation. DSM programs and techniques are reviewed in [2-4, 43]. In literature, there are two DSM method categories: control-based approach and market-based approach, which are discussed in the following sections.

2.2.3.1. Control-based Approach

2.2.3.1.1. Direct Load Control

Direct Load Control (DLC) manages demand side directly over a certain period, normally in a short notice [37]. The load consumption is shifted or interrupted during the time of control. For residential customers, DLC allows consumers' energy consumption to be remotely managed [6]. Normally interruptible loads, such as thermostatically controllable loads (water heaters, air conditioners and etc.), are controlled under DLC [44, 45], as they are seen as flexible load devices that can be scheduled and interrupted for several hours during peak time [46]. Incentives can be offered to consumers so to attract their willingness to participate in the DLC. For example, energy credits are rewarded to customers under DLC in [44], based on their contribution during a DSM event. Some of the DLC aims to use the load services to provide a certain amount of ancillary services (such as reserve and frequency regulation) and enhance the reliability of the electric system through offering back – up support during generation outages [45-47].

2.2.3.1.2. Indirect Control

Indirect control (IC) approaches use incentive signals to entice customers to change their behaviour corresponding to the incentive signals [7]. The most common incentive signals are price signals, and it normally refers to the price-based approaches. In recent years, customer-centred approaches are starting to emerge. This research categorises the customer-centred approach in the IC group. These two approaches are reviewed in the following sections.

2.2.3.1.2.1. Price-Based Approaches

Under price-based approaches, customers change their electricity usage patterns in response to the price signals they receive. They shift their consumption towards low electricity prices time periods, in order to reduce their energy payment. Various price tariffs are introduced below, which are Time of Use (ToU) price, Critical Peak Pricing (CPP) tariff and Real-Time Pricing (RTP).

ToU Pricing: ToU pricing has varying electricity prices during different time periods in a day [48, 49]. The electricity pricing signal sent to consumers will be higher during peak time. In contrast, lower prices will be configured for off-peak time periods. The electricity price rates of ToU are designed based on the production and utility cost structure and the rates are not associated with real-time electricity prices in the electricity market [48, 50, 51]. In some European countries, ToU pricing techniques have already practised in some residential households, notably in households with electric heating devices [52]. The impact of ToU pricing on the behaviours of residential demand in Northern Italy is discussed in [51]. It was observed that residential customers are able to react to the time-varying price tariff and their energy bill costs are reduced by 2.21%, although their energy usage increased by 13.69%. Residential demand system including a plug-in EV is built in [53]. The demand response of the residential system to a two-tier ToU pricing was simulated. Similar to [51], it is found that the residential demand is able to shift their consumption to the period when the price drops. Furthermore, a multi-ToU paradigm is proposed in [53], which sends different ToU tariffs to different customer groups, so to avoid creating a new peak when ToU prices are low. In addition to benefit customers with lower costs using ToU pricing, [54] explores the potential capability of using aggregated electric water heaters to balance wind generation.

Economy 7 tariff is one of the most common ToU pricing tariffs in UK households. The tariff is only suitable for electricity type bills, not for gas consumption. Most electricity suppliers are offering Economy 7 tariff, and the electricity price in the tariff is discounted for seven hours in midnight time when compared to standard daytime prices [55]. The aim of proposing and applying Economy 7 tariffs in the UK is to shift a certain amount of load towards off-peak periods. To carry out Economy 7 tariffs in individual households, an electricity meter with two-rate radio tele-switching capability is required to be installed as an enabler.

Critical Peak Pricing (CPP) Tariff: CPP is a combined tariff between ToU pricing and higher rates during critical peak periods with very high demand in the system [49]. A case study of Critical Peak Pricing (CPP) has been carried out in California to analyse customer response [56, 57]. The CPP tariff was applied to large residential consumers who were equipped with automated air-conditioning responses, and the peak electricity price rates were configured as three times higher than the ToU peak rates. A 5-hour and 2-hour critical peak period were applied to the participating residential households. The results showed a reduction in load during these two periods by 25% and 41%, respectively. Moreover, it concluded that a 5% reduction in the peak demand in California is possible, with smart metres and dynamic price tariffs.

Real-Time Pricing (RTP) Tariff: The electricity prices of RTP vary during the time over a day, and the price rates are determined by market clearing prices[49, 52, 58]. Thus, the varying RTP electricity price rates at different time durations can reflect the network conditions, for example, the amount of wind generation that injects into the grid at a particular time period. Different demand response models of RTP tariff are proposed in [59, 60]. The real-time demand response model developed in [59] updates customer’s responses according to updated hourly RTP rates. The uncertainty of the prices is modelled using a robust optimisation model with bounded values. In [60], a home energy management scheduler is built to reduce the energy consumption cost when customers are facing RTP. The scheduler detects available appliances and schedules the appliances in response to the RTP. In addition, the future impact of demand scheduling using RTP on the GB network are studied in [61]. It concluded that a peak demand reduction of 8-11GW can be achieved in the UK when there is low wind generation, under a future UK scenario with a 15GW wind penetration. Customers who want to sign up to RTP tariff will require a smart meter [62] or new ICT infrastructure [11]. The installation fee of a smart meter is normally covered by the utility companies and consumers pay for the cost of their meter and its maintenance through their energy bills monthly [63].

2.2.3.1.2.2. Customer-Centred Control

The European Commission proposed the Clean Energy for All Europeans Package (also known as the Winter Package) on 30 November 2016 [64]. In the Clean Energy for All Europeans Package, it is proposed to be a customer centred clean energy transition, which will give consumers more controllability on their own energy consumption, energy choices and energy costs, through deploying smart metres and market-based electricity pricing [10].

Customer-centred control has started to emerge in recent years. Customers engaged through customer-centred control are able to impose their energy usage preferences when their devices are being controlled. In contrast to the DLC, the consumer-centred approach schedules end-users' devices based on customers' preferences and predefined daily electricity consumption patterns. This means that consumers are taking control of their home appliances. Nowadays, customers are able to switch on and off their smart appliances through using a smartphone app, such as the HIVE app [14] that were innovated by British Gas. A demand response framework for managing residential HVAC (Heating, Ventilation, and Air Conditioning) is proposed in [65], which considers customers' thermal comfort with price uncertainty. A balance is maintained between customers' cost minimisation and comfort satisfaction in [66], by using an energy disaggregation algorithm to determine load characteristics based on historical data. Furthermore, a residential management model that ensures customers' satisfaction is developed in [67] to regulate voltage and network losses in part of the Egyptian distribution network.

Customers who participate in the customer-centred control receive external signals to which they may or may not respond. As aforementioned, a typically external signal is a pricing signal [65-67]. In addition to pricing signals, RSE has developed and tested a prototype customer-engaging system [16], which is able to notify suggestions for demand scheduling to customers and check if the suggestions have been accepted by the customers.

2.2.3.2. Market-Based Approach

Demand side customers are able to participate in energy markets to assist in balancing the network on a system level. This typically refers to large customers and aggregated residential customers. Under the market-based approach, customers submit bids to energy markets, which indicate the energy that they will be able to increase/reduce at a certain time. If a customer's submitted bid is accepted, it is expected that the customer will increase/reduce an agreed amount of consumption at the requested time, as indicated in the bid. The customers will then receive payment if they've delivered the agreed amount of energy at the requested time. The purpose of the market-based approach is to keep the balance between supply and demand.

Demand bidding program in the US electricity market is one of the examples of the market-based approach. Time shiftable load can bid optimally in electricity markets (the day-ahead market and real-time market) in the US by submitting one aggregated bids or several sub-bids, using the method proposed in [68]. A demand bidding algorithm is presented in [69], which reduces their demand when the network is constrained while increases the profits of the large manufacturing load.

In the balancing market in the UK, which is operated and managed by National Grid (NG) Electricity System Operator (ESO), it has a number of services in which demand side customers can participate [13]. These include Short Term Operating Reserve (STOR), fast reserve and frequency response. Detailed opportunities for demand response customers in the UK balancing market is illustrated in [70]. To provide demand response services to the balancing market, small customers are required to be viable and competitive in the scale of demand side responses. Therefore, NG ESO requires the aggregation of small customers. The participated customers will receive payments for providing demand response services.

2.2.4. DSM Challenges

DSM technologies have already been proposed and trialled. However, there still exist some challenges that limit/slow the process of its rollout.

As stated above, the application of DSM will benefit different layers in the electric power system. Customers are the most important part that enables the DSM. The willingness of engagement from the customers decides how the DSM program will progress [71]. However, people do not understand the benefits and impacts of DSM technologies. Benefits and results of the DSM programs should be quantified and passed onto the consumer. Moreover, customers need to be assured they would be able to keep their comfort level. Another concern of customers who hesitate to join the DSM is data security, which may be overcome in [72] which proposes to anonymize the identity of the metering data.

Smart meters are playing a relatively important role as the enabler for the DSM programs. However, the implementation percentages of smart meter installations in UK residential households are very low so far. The overall progress, by the end of June 2018, has 13.55 million gas and electricity smart meter installed, comparing to the government goal of rolling out over 50 million gas and electricity smart meters by 2020 [73]. A detailed introduction of smart meters can be found in section 2.2.5. Lacking information communications is another barrier to the application of DSM technologies. Two-way information communications are necessary.

The traditional way of power system operation is to provide sufficient reserve and supply adequate generation capacities in order to ensure the security of supply and prevent generation shortages. It is expected that the application of DSM technologies will increase the system operation complexity compared to the traditional method. This is another difficulty that needs to be tackled for DSM. However, DSM flexibilities are vital in solving the problem of increasing uncertainty in the future power grid, e.g. improving the utilisation of intermittent renewable generation and reduce curtailment.

Thinking of the GB market structure, implementing DSM may bring conflicts of interests with involving parties in the market. The system operator normally goes to the balancing market in the UK when the network is facing congestion, imbalance, etc. Balancing Service Providers (BSP) receive payments for providing services to the balancing market. As DSM could avoid congestions and balance between generation and consumption [6, 27, 28], BSP will suffer a loss in revenue. In addition, it needs to be clear who is in charge of controlling the DSM customers, as DSM customers cannot receive signals from different network parties. An aggregator might ask customers to increase their demand so to take advantage of the surplus distributed renewable energy, while a network (system) operator may require customers to reduce their demand for a short period due to network congestions [12]. Therefore, different business cases are required for each individual network stakeholders with the application of DSM.

2.2.5. Smart Meter – DSM Enabling Technology

The UK government has established a central change programme, which aims to roll out over 50 million gas and electricity smart meters to all homes and small businesses in GB by the end of 2020 [73]. In the same way as the traditional meters charges, customers will cover the cost of installation and maintenance of smart meters through energy bill payments. Up to the end of June 2018, 13.55 million gas and electricity smart meters were installed in domestic households and smaller non-domestic businesses, with most of them were installed by large suppliers. Among the 13.55 million smart meters installed, there were over 12 million operating across domestic properties and small businesses in GB [73].

Smart meters offer a range of intelligent functions. One major function is it enables data communications. Customers therefore will not need to manually submit readings or pay for estimated bills, since real-time energy usage information can be collected. However, it means internet connections are essential to enable remote communications of smart meters. A monitor usually comes with the installation of the smart meter, the most common type of display is presented in Figure 2-5 [74]. The display could show the energy consumed and total electricity bill costs for a day. The smart meter monitors allow customers to set their budget level for a day, and the display could tell customers how much budget has been consumed. With the intelligent monitoring function of smart meters, customers would be able to better manage their energy use if they are willing to. Smart meters can also be suitable for pre-payment customers, so pre-payment customers could actively monitor the remaining credit and also set reasonable budgets for daily energy usage.

Suppliers would be able to innovate tailored tariffs to customers by assessing the usage patterns, through energy usage data remotely provided via smart meters. This could increase the diversity of energy tariffs in the UK. The smart meters could also be combined with RTP tariffs if this tariff is introduced into the GB market. Customers signed up to RTP could actively monitor the energy rates at different times a day so to conduct heavy energy use activities during times when prices are low. Network (system) operators could also use RTP price rates as indicators, for example, to entice customers to consume more energy when there is surplus renewable energy by offering low energy price rates.

Figure 2-5 Smart Meter Monitors [74]

As a result, smart meters play a vital role in enabling data information communications. They are now regarded as communication enablers/hubs which could be combined with DSM techniques, to control the demand consumption.

2.3. DSM Trials

There are a number of DSM trials completed and underway across the world. The DSM trials look to investigate demand side flexibility for network operation.

In the US, the Olympic Peninsula project [75] tested the impact of various electricity pricing signals on end-users via two-way communication. RTP was tested in the Energy Smart Pricing Plan project with 1,500 participants in Illinois [76] to demonstrate the potential of using RTP as a retail tariff option.

Across the EU, ADDRESS [77] developed solutions to engage domestic and small commercial customers and prosumers, to allow sustainable renewable growth. Sim4Blocks [78, 79] investigates the potential of demand responses from buildings to enable better integration of renewable energy, across three pilot sites in Switzerland, Spain and Germany. It also aims to develop business models of demand response for market access. A near real-time optimal commercial and industrial demand response system with a novel market framework is being developed by eDREAM [80, 81].

In the UK, there are innovation activities on demand flexibility carried out by distribution network operators. The NINES project [82] used an active network management system that integrates domestic demand side management and energy storage system to increase the utilisation of renewable distributed generation and reduce renewable curtailment. The SAVE (Solent Achieving Value from Efficiency) project [83] explored energy efficiency measures to manage the peak demand as an alternative to network reinforcement. Energywise [84] trialled ToU pricing on vulnerable customers to engage them for energy savings. To move from trials to business as usual deployment, the ENTIRE project [85], which is built on learnings from FALCON [86], investigated if a wide-scale application of DSM can support Business as Usual operation.

The trials and projects have shown the potential of residential customers to alter consumption and benefits network operation when required. Details of the Olympic Peninsula, the ADDRESS, the NINES project and their key findings are discussed in Appendix I.

2.4. Summary

To achieve Net Zero target set by the UK government, challenges arise when operating the network. Flexibility is therefore required for network operation and demand side can provide a certain level of operational flexibility. DSM technologies enable customers to provide flexibility. Two categories of DSM approaches are reviewed in this chapter, which are control-based and market-based approaches. DSM opportunities together with challenges are also discussed in this chapter. DSM pilot trials in the US, EU and UK are reviewed briefly with details and findings presented in Appendix I. The reviewed projects have illustrated that DSM is able to benefit network operation.

Chapter 3
Residential Demand-Centred Scheduling Tool

3.1. Introduction

The changes undergoing in the power system nowadays are typically associated with shifts towards a more flexible decentralised operation, and a particular emphasis on the operational flexibility could be coming from the demand side in the energy network. Through applying DSM technologies, reduced peak demand, improved utilisation of renewable energy and deferred network investment can be achieved. In addition, DSM can also benefit customers with energy bill savings.

DSM covers a broad range of techniques, which are reviewed in section 2.2.3. Typically, DLC is used to schedule customer responses, where demand e.g. home appliances, are reacting to direct remote control signals sent by network/system operators or on changes in system wide parameters such as a system frequency. Thus, under DLC scheme home appliances are scheduled and controlled by an external entity and typically with relatively short notice. Under current pilot trials (as aforementioned in section 2.3), DLC is typically carried out on frequency–responsive load devices, e.g. air conditioners and heating devices etc. Implementation of DLC, however, may necessitate an evaluation of consumers' tolerance levels towards these direct external interventions, especially if various groups of home appliances are affected.

In order to overcome perceived intrusiveness of DLC approaches which may discourage some customers to take part in such programs [71], customer-centred methods where customers receive external signals to which they may or may not respond have started to emerge. An approach that enables customers to take part and help them decide how to schedule various appliances within the household is introduced. In contrast to the external DLC, the consumer-centred approach schedules end–users' devices based on customers' preferences and predefined daily electricity consumption patterns. This means that consumers are taking control of their home appliances and all of the decisions are made so to achieve objectives of customers. It is important to acknowledge that such an approach may significantly improve customer engagement and consequently increase the energy savings of residential households if customers seek to improve energy efficiency and reduce energy waste.

The customer-centred approach typically uses price signals that are straight forward and easier to adapt to. Results of the trials (available in Appendix I) employed price signals showed a successful demand shifting and peak reduction. The results also indicated the potential of residential loads being regarded as a group that should be further investigated to provide demand flexibility.

3.2. Customer-Centred Scheduling Tool

As a bottom-up approach, the customer-centred approach relies on customers to make their own decisions regarding when and how much energy to consume. However, it may not be an easy task for an average household, and thus help the customers to engage is one of the important areas to consider during the development of the tool.

A customer-centred scheduling tool [87] that enables participating customers to automatically respond to the inflow price signals is built in this research. The inflow price signals may vary during a day. The tool seeks to support automatic scheduling of household appliances and to minimize the cost of energy to the customers while ensuring that preferences stemming from their lifestyle choices and a need to supply at least certain pre-specified amount of energy are respected. It assumes that the customers are participating in the customer-centred program where price signals are sent by system operator/aggregators with expectations that the customer will modify their consumption based on these prices. Therefore, it decides on when household appliances will be scheduled based on consumers' preferences.

Typically, assuming the availability of smart meters is regarded as enabling technology for the implementation of the scheduling tool in individual households, as illustrated in Figure 3-1. The UK government has established a central change programme, which aims to roll out 53 million gas and electricity smart meters to all homes and small businesses in GB by the end of 2020 [88]. Therefore, the smart metres could be used for the bi-directional communication between suppliers or aggregators and customers, to bring necessary signals and information to customers and also be used to monitor consumption and response to signals.

The customer-centred scheduling tool is the main component of the 'intelligence box' (in Figure 3-1) attached to the smart meter and installed into each individual household. Inflow price signals are sent by suppliers or aggregators which seek to influence demand at particular time periods. For example, if connected wind generators are facing curtailment due to network constraints, the aggregator may seek to increase the consumption of some customers. Under such circumstance, reduced energy price will be sent to these customers so that they could alleviate renewable curtailment. Consumers in the household can choose whether they are willing to respond to price signals and if so, they could achieve savings in their electricity bills. If a customer incline to actively participate in the DSM scheme, the customer could input preferences and the load devices will be automatic and intelligently rescheduled based on the customer's own requirements. The aim of the tool is to help consumers reduce their energy payments, and fulfil their consumption needs at the same time.

Figure 3-1 Illustration Of Demand Response Scheduling Tool Application

3.2.1. Residential Households Energy Consumption

The challenge of the scheduling tool, which uses the customer-centred approach, is to meet consumers' various needs during different time periods, as well as to ensure that the total energy requirement for a specified period of time is met. The consumption preferences should be allocated to each home appliance, and consumers' electricity usage behaviours should be investigated and considered. Decomposition of major home appliances attributes to the UK demand curve is given in Figure 3-2 [89]. It also includes the total amount of energy usage over a day. For example, among the decomposed loads in Figure 3-2, the peak energy usage of electric water heater occurs during morning and evening time periods – before and after working hours. While the energy consumption in the load curve for the washing machine keeps high between around 8 a.m. to 8 p.m.

The components of household energy demand during a typical winter peak is shown in Figure 3-3 [90]. Cooking appliances, lighting, and standby devices (e.g. TVs, videos and stereos) use 37.6%, 15.7%, and 5% of the peak energy consumption, respectively. These usages cannot be shifted easily, especially lighting as customers will not tolerate living in dark. Fridges and freezers absorb 9% of the peak consumption. They could be switched off for a period of time during the peak, considering the space in the cold appliances is able to maintain the temperature for a short duration. Wet appliances (including dishwashers and washing machines) and electric water heater consume 6% and 16.5% peak energy, respectively. The wet appliances and electric water heater can be shifted to off peak time when the consumption is low.

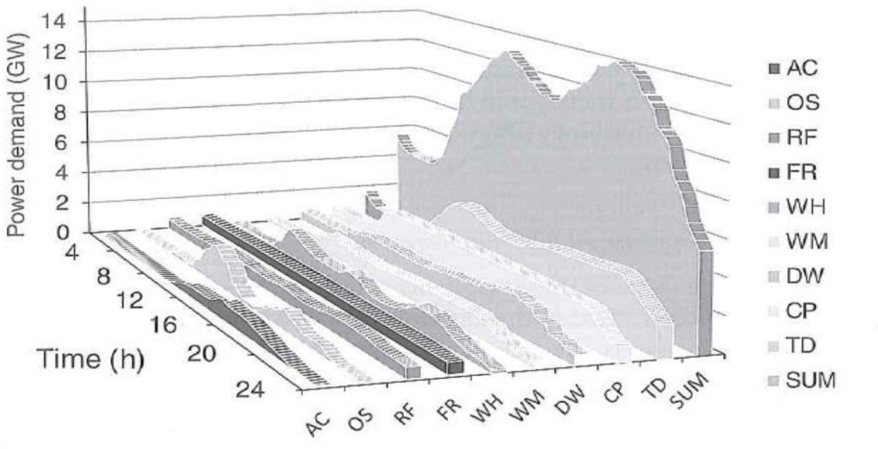


Figure 7.3 Total demand from domestic appliances in the UK. Notes: AC = air conditioner; OS = over and stove; RF = refrigerator; FR = freezer; WH = electric water heater; WM = washing machine; DW = dishwasher; CP = heating circulation pump; TD = tumble dryer; SUM = sum of all appliances.

Figure 3-2 The UK Home Large Appliances and Demand Curve [89]

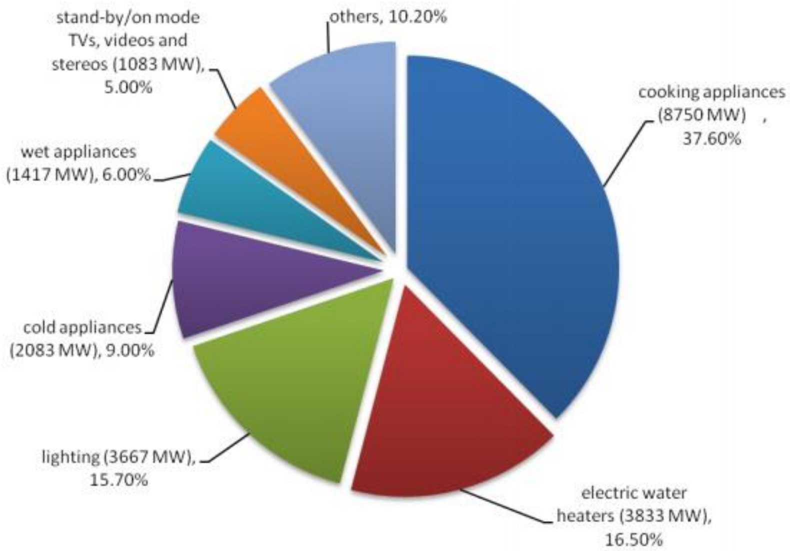


Figure 3-3 The Components of Household Energy Demand at System Peak [90]

It can be concluded from Figure 3-3 that at least 22.5% of the UK home appliances (wet appliances and electric water heaters) could be scheduled/shifted towards off-peak time as long as customers' living expectations are not affected by the scheduling, which means a potential of 22.5% peak reduction. Alternatively, home devices could be planned to run at time periods when the renewable generators are facing curtailments. This could benefit the UK electric system with improved operational flexibility.

3.2.1.1. Flexibility Level of Home Appliances

Different home appliances have various level of scheduling flexibility relevant to consumers' energy usage patterns. The customer-centred scheduling tool will consider information on the contribution of each load devices to the rescheduling, through investigating the load flexibility level. Note that here flexibility is regarded as the availability to be rescheduled. Moreover, the impact of scheduling constraints of the controlled loads on consumers' life is a criterion for the flexibility level as well. These constraints are controlled via input parameters that are specified by the consumer in this research, and they can be changed to reflect different preferences. The level of scheduling flexibility for end–user devices are divided into three categories – high, medium, and low level. In the low schedule flexibility category, it includes low and zero flexibility home appliances.

High scheduling flexibility home appliances refer to end–user devices with high schedule availability, which could respond to the DSM signals in a relatively short time slots with fewer operation constraints attached. If power connections of the high scheduling flexibility devices are temporarily disconnected, the functions that home appliances are expected to deliver can still be achieved [91]. For example, electric water heating, air conditioning and space heating can be categorised as high scheduling flexibility appliances. One special case of this type of loads is refrigerator/fridge and freezer. Because of the relatively sufficient food preservation room space in fridge and freezer, the temperature in the refrigerator could be maintained at an acceptable level if the electric supply only switches off for a short time duration. Moreover, loads with their own electric storages/batteries installed are expected to be classified as high flexibility devices, e.g. EVs, laptops, mobile phones, tablets and other electronic equipment with built-in batteries. The high scheduling flexibility home appliances are usually the first choice when there is a requirement for DSM. Typically, consumers are unaware of when high flexibility loads are being scheduled by DSM signals.

Medium scheduling flexibility home appliances are load devices with lower scheduling availability when compared to high scheduling flexibility appliances. The medium scheduling flexibility loads could respond to DSM signals when it is available, as this kind of appliances has certain operational constraints for the DSM application. Customers can still accept DSM control on the medium scheduling flexibility devices so long as the function and quality delivered by the appliances can fulfil the consumers' electricity usage needs and expectations [91]. For example, washing machine, tumble dryer and dishwasher could be sorted as medium scheduling flexibility loads. Figure 3-4 [92] presents a social survey regarding potential load shifting according to the electricity price rates sent to residential households. It summarises responses of customers to the questionnaire on the activities they are engaged during 7-9 p.m. and activities they are willing to shift after 9 p.m. As Figure 3-4 shows, 28.4% and 18.4% respondents use washing machines and dishwashers between 7 and 9 p.m., and 65.2% and 37.5% are willing to shift their activities of using washing machines and dishwashers after 9 p.m., respectively. Therefore, the electricity usage and energy service of medium scheduling flexibility appliances could be shifted and rescheduled to another time period, as long as customers can have the items ready when they expected them to be.

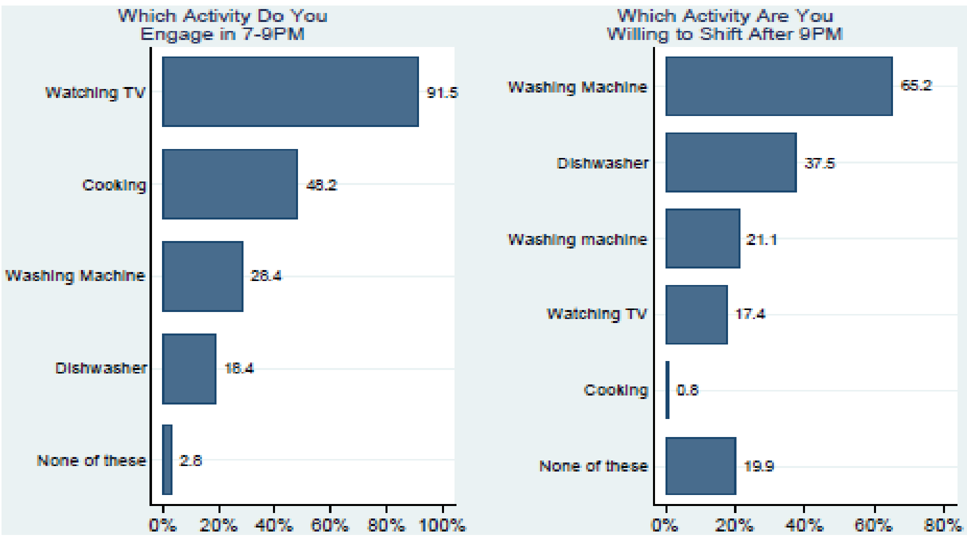


Figure 3-4 A Social Survey on Potential Load Shifting [92]

Low scheduling flexibility home appliances are the home appliances that could provide comparatively low schedule availability or zero possibility for scheduling. The low flexibility appliances group can only respond to DSM signals if it does not cause inconvenience to consumers' lives. While the type of zero flexibility loads is not available to be scheduled and will not respond to DSM signals [4], as the constraints attached to the zero flexibility load appliances do not allow them to be shifted. Cooking devices, vacuum cleaners, hairdryers, microwaves and ovens are classified as low scheduling flexibility home appliances. If DSM is applied to the loads, the impact on consumers' electricity usages can be observed immediately. For example, if the cooking process is interrupted, the cooking time and food quality will be affected. Cooking activities are rated 48.2% as an activity to engage at 7-9 p.m. by survey respondents in Figure 3-4, however, only 0.8% of customers indicated the willingness to shift their cooking activities after 9 p.m. For the zero scheduling flexibility home appliances, the electricity usage pattern is strict and no changes will be available for DSM. If DSM is applied to the zero scheduling flexibility devices, it will cause immediate interruption for delivery of the service and loss of functionality. Home entertaining equipment, such as TVs, DVDs, and etc., are regarded as zero scheduling flexibility loads. Over 90% of customers (of the survey in Figure 3-4) watch TV during 7-9 p.m., with 17.4% of respondents can accept to shift the activity after 9 p.m. As a result, when there are requirements regarding the services of the low scheduling flexibility home appliances in the household, the energy service should be enabled. The zero flexibility load appliances cannot be engaged in DSM at all.

3.2.2. Methodology

The basic customer-centred scheduling tool developed in this research is a mixed-integer linear optimisation problem [93], which aims to optimise the scheduling of home appliances in order to minimise their energy cost, when they are facing ToU (Time of Use) pricing. Fico Xpress optimization software [94] is used to solve these optimisation problems. Thus, through optimised scheduling, appliances are scheduled towards lower price period and customers can benefit from lower energy bill payment. At the same time, the schedule of home appliances is based on consumers' energy usage preferences. Customers' energy usage needs are therefore being fulfilled.

The overall objective of the basic scheduling tool is to minimise customers' bill payment. Several constraints are considered in the optimisation problem, including

- Total energy consumption allowance: constraints on total household consumption level,
- Home appliances constraints: constraints related to appliances that consider initial statuses of home appliances and customer's comfort settings,
- Energy storage device constraints: energy storage charging/discharging and capacity constraints,
- PV constraints: PV capacity and production constraints,
- EV constraints: EV capacity constraint, EV charging time and rate constraints,
- Storage heater constraints: Storage heater charging (heating up) and discharging (heat dispensing) constraints, and heating comfort settings.

Seven virtual household models are simulated with the same objective but different combinations of the above devices and constraints. The following sections introduce the 7 case studies in detail.

3.2.3. Case Studies

Seven virtual residential household systems are carried out for testing the basic scheduling tool. The devices included in the seven households are listed below and summarized in Table 3-1. The mathematical formulation of each house models are presented in section 3.2.3.1 to 3.2.3.7.

- House A includes seven typical home appliances, which are an electric water heater, a washing machine, cooking devices, a dishwasher, a fridge freezer, a space heating, and a TV. The seven home appliances are selected from different scheduling flexibility levels, as discussed in section 3.2.1.1.
- House B includes the seven home appliances and one energy storage device.
- House C includes the seven home appliances, one energy storage device and Photovoltaic (PV) panels. The PV energy can be used to directly supply the house and/or be stored in the energy storage to use solar energy later.
- House D includes the seven home appliances, one energy storage device and PV panels. The PV energy can be used for self-consume within the house, be

stored in the energy storage, and/or be exported back to the grid. Moreover, the energy storage can also export its stored energy to the energy network.

- House E includes the seven home appliances, one energy storage device, one Electric Vehicle (EV) and PV panels. The same as House D, the PV and energy storage can export energy back to the network.
- House F includes six home appliances, one energy storage device, one storage heater and PV panels. House F replaces the space heating with a storage heater, which has ability to store heat. The PV and energy storage can choose to sell their energy to the grid to earn payments.
- House G includes the six home appliances, one energy storage device, one storage heater, one EV and PV panels. The same as House E and House F, the energy storage and PV can export their energy back to the grid.

Table 3-1 Summary of Virtual House Systems and Devices in the Houses

Virtual Households	Household devices
House A	seven home appliances
House B	seven home appliances + one energy storage device
House C	seven home appliances + one energy storage device + PV panels (self-consume)
House D	seven home appliances + one energy storage device + PV panels (Energy storage and PV are able to export energy)
House E	seven home appliances + one energy storage device + one EV + PV panels (Energy storage and PV are able to export energy)
House F	six home appliances + one energy storage device + one storage heater + PV panels (Energy storage and PV are able to export energy)
House G	six home appliances + one energy storage device + one EV + one storage heater + PV panels (Energy storage and PV are able to export energy)

3.2.3.1. House A

Objective function:

$$\underset{t}{Minimise}\, COST = \sum_{t=1}^{T} \{P(t) * \pi(t)\} \tag{3-1}$$

Subject to**:**

$$P(t) = \sum_{i=1}^{I} P_i u_i(t) \qquad \forall i, \forall t \in T \tag{3-2}$$

$$P_{min}(t) \leq P(t) \leq P_{max}(t) \qquad \forall t \tag{3-3}$$

$$T_{i.\ ON} \geq \begin{cases} T_{i.\ op} & \\ T_{i.\ op} - t_{ON.ini} & if\ u_{i.ini}(t=0) = 1 \end{cases} \qquad \forall i, \forall t \tag{3-4}$$

$$T_{i.\ OFF} \leq \begin{cases} T_{i.\ off}^{max} & \\ T_{i.\ off}^{max} + t_{ON.ini} & if\ u_{i.ini}(t=0) = 0 \end{cases} \qquad \forall i, \forall t \tag{3-5}$$

$$U_{i\ ON} = 1^{T} * u_i(t) \qquad \forall i, \forall t \tag{3-6}$$

$$U_{i\ ON}^{min} \leq U_{i\ ON} \leq U_{i\ ON}^{max} \qquad \forall i \tag{3-7}$$

$$u_i(t) \in [0,1] \qquad \forall \mathrm{i}, \forall \mathrm{t} \tag{3-8}$$

$$u_{i.ini}(t=0) = \begin{cases} 0 & t_{ON.ini} \leq 0 \\ 1 & t_{ON.ini} > 0 \end{cases} \qquad \forall i, \forall t \tag{3-9}$$

As noted above in Section 3.2.3, House A has seven typical home appliances. Equation (3-1) defines the aim of the basic scheduling tool is to minimize the consumers' energy bill payments. The tool optimises when the home appliances will run. The decision progress considers several aspects including the total energy consumption allowance (3-3), the minimum operating durations of each home appliance (3-4), the maximum off duration (3-5), and the total running time limit (3-7). Equation (3-2) calculated the total energy consumption $P(t)$ in the household at each time slot of scheduling. The overall consumption limitations are defined in equation

(3-3), which is used to limit the amount of power $P(t)$ that a household can draw at any instant in time. Some appliances have their minimum operating time $T_{i.\ op}$ and maximum switching off $T_{i.\ off}^{max}$ durations, which are enforced in equation (3-4) and (3-5). These periods refer to continue working $T_{i.\ ON}$ or switching off time $T_{i.\ OFF}$ durations of the appliances. For instance, a washing machine has cycles which should not be interrupted once started. The minimum operating and maximum switching off time also respect the initial statuses $t_{ON.ini}$ of the home appliances, since it is impossible to set every device back to power off status when the scheduling starts. The initial statuses are used as inputs. The total running time $U_{i\ ON}$ of each home appliance is calculated in equation (3-6), and the limitations of the total running time are defined in (3-7). A binary variable $u_i(t)$ in (3-8) is used to decide the on/off activity for the devices that are scheduled by the tool. Moreover, the binary variable $u_{i.ini}(t=0)$ in equation (3-9) indicates the initial statuses of appliances, i.e. the on/off status of appliances at the beginning of the scheduling process. Note that parameters in all of these constraints are decided by consumers. They can be set as inputs into the scheduling tool. For example, the cooking devices are assumed to operate during the evening (after working hours) for a few hours.

3.2.3.2. House B

Objective function:

$$\underset{t}{Minimise}\, COST = \sum_{t=1}^{T} \{P(t) * \pi(t)\} \tag{3-10}$$

Subject to**:**

$$P(t) = \{\sum_{i=1}^{I} P_i u_i(t)\} + P_{s.char.grid}(t) - P_{s.dischar.app}(t) \quad \forall i, \forall t \in T, \forall s \tag{3-11}$$

$$P_{min}(t) \leq P(t) \leq P_{max}(t) \qquad \forall t \tag{3-12}$$

$$T_{i.\ ON} \geq \begin{cases} T_{i.\ op} & \\ T_{i.\ op} - t_{ON.ini} & if\ u_{i.ini}(t=0) = 1 \end{cases} \qquad \forall i, \forall t \tag{3-13}$$

$$T_{i.\ OFF} \leq \begin{cases} T_{i.\ off}^{max} \\ T_{i.\ off}^{max} + t_{ON.ini} \quad if\ u_{i.ini}(t=0)=0 \end{cases} \qquad \forall i, \forall t \qquad (3\text{-}14)$$

$$U_{i\ ON} = 1^{T} * u_i(t) \qquad \forall i, \forall t \qquad (3\text{-}15)$$

$$U_{i\ ON}^{min} \leq U_{i\ ON} \leq U_{i\ ON}^{max} \qquad \forall i \qquad (3\text{-}16)$$

$$u_{s.char}(t) * P_{s.char}^{min}(t) \leq P_{s.char.grid}(t) \leq u_{s.char}(t) * P_{s.char}^{max}(t) \quad \forall s, \forall t \quad (3\text{-}17)$$

$$u_{s.dischar}(t) * P_{s.dischar}^{min}(t) \leq P_{s.dischar.app}(t)$$
$$\leq u_{s.dischar}(t) * P_{s.dischar}^{max}(t) \quad \forall s, \forall t \quad (3\text{-}18)$$

$$\mathrm{SOC}_s(t) = \mathrm{SOC}_s(t-1) + P_{s.char.grid}(t) - P_{s.dischar.app}(t) \quad \forall \mathrm{s}, \forall \mathrm{t} \quad (3\text{-}19)$$

$$\mathrm{SOC}_s(t)^{min} \leq \mathrm{SOC}_s(t) \leq \mathrm{SOC}_s(t)^{max} \qquad \forall t \qquad (3\text{-}20)$$

$$u_i(t) \in [0,1] \qquad \forall \mathrm{i}, \forall \mathrm{t} \qquad (3\text{-}21)$$

$$u_{i.ini}(t=0) = \begin{cases} 0 & t_{ON.ini} \leq 0 \\ 1 & t_{ON.ini} > 0 \end{cases} \qquad \forall i, \forall t \qquad (3\text{-}22)$$

$$u_{s.char}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \qquad (3\text{-}23)$$

$$u_{s.dischar}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \qquad (3\text{-}24)$$

$$u_{s.char}(t) + u_{s.dischar}(t) = 1 \qquad \forall s, \forall t \qquad (3\text{-}25)$$

House B includes seven home appliances and one energy storage device. The objective of scheduling House B is to minimise the cost of the customer's energy bill as well, as illustrated in equation (3-10). The energy consumed in House B in equation (3-11) considers the energy consumption of the home appliances $\sum_{i=1}^{I} P_i u_i(t)$, and also the charging $P_{s.char.grid}(t)$ and discharging $P_{s.dischar.app}(t)$ activities of the energy storage. The energy storage can charge from the grid supply and discharge to supply the home appliances. Similar to House A, the scheduling constraints involved for the home appliances are the total consumption allowance (3-12), the minimum operating durations of each home appliance (3-13), the maximum off duration (3-14), and the total running time periods limit (3-16). Equation (3-17) and (3-18) expresses the upper and lower levels of charging and discharging power per hour of the storage device. The State Of Charge (SOC) of the energy storage $\mathrm{SOC}_s(t)$ is related to the charging $P_{s.char.grid}(t)$ and discharging $P_{s.dischar.app}(t)$ activities, as well as previous SOC state $\mathrm{SOC}_s(t-1)$, which is computed in (3-19). Since different energy storage has different capacity, the limitations of the maximum and minimum SOC are defined in equation (3-20). Binary variables in (3-21) and (3-22) indicate the on/off and initial statuses for the appliances, respectively. Additional binary variables $u_{s.char}(t), u_{s.dischar}(t)$ defined in (3-23) and (3-24) are used for implying the charging and discharging status of the energy storage device. Thus the charging/discharging status of storage is determined by the scheduling tool, with only one of these activities can be active at one time, as defined by equation (3-25).

3.2.3.3. House C

House C has seven home appliances, one energy storage device and PV panels. In House C, the energy generated by the PV panels is consumed inside the house.

Objective function:

$$\underset{t}{Minimise}\, COST = \sum_{t=1}^{T} \left\{P(t) * \pi(t) - P_{pv}(t) * \pi_{FIT.gen}(t)\right\} \tag{3-26}$$

Subject to**:**

$$P(t) = \left\{\sum_{i=1}^{I} P_i u_i(t)\right\} + P_{s.char.grid}(t) - P_{s.dischar.app}(t) - P_{pv.ds}(\mathrm{t})$$

$$\forall i, \forall s, \forall pv, \forall t \in T \tag{3-27}$$

$$P_{min}(t) \le P(t) \le P_{max}(t) \qquad \forall t \tag{3-28}$$

$$T_{i.\ ON} \ge \begin{cases} T_{i.\ op} & \\ T_{i.\ op} - t_{ON.ini} & if\ u_{i.ini}(t=0) = 1 \end{cases} \qquad \forall i, \forall t \tag{3-29}$$

$$T_{i.\ OFF} \leq \begin{cases} T_{i.\ off}^{max} \\ T_{i.\ off}^{max} + t_{ON.ini} \quad if\ u_{i.ini}(t=0)=0 \end{cases} \qquad \forall i, \forall t \tag{3-30}$$

$$U_{i\ ON} = 1^{T} * u_i(t) \qquad \forall i, \forall t \tag{3-31}$$

$$U_{i\ ON}^{min} \leq U_{i\ ON} \leq U_{i\ ON}^{max} \qquad \forall i \tag{3-32}$$

$$u_{s.char}(t) * P_{s.char}^{min}(t) \leq P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t)$$
$$\leq u_{s.char}(t) * P_{s.char}^{max}(t) \quad \forall s, \forall t \tag{3-33}$$

$$u_{s.dischar}(t) * P_{s.dischar}^{min}(t) \leq P_{s.dischar.app}(t)$$
$$\leq u_{s.dischar}(t) * P_{s.dischar}^{max}(t) \quad \forall s, \forall t \tag{3-34}$$

$$\mathrm{SOC}_s(t) = \mathrm{SOC}_s(t-1) + P_{s.char.grid}(t) - P_{s.dischar.app}(t) + P_{s.\mathrm{pv}char}(t)$$
$$\forall \mathrm{s}, \forall \mathrm{t} \tag{3-35}$$

$$\mathrm{SOC}_s(t)^{min} \leq \mathrm{SOC}_s(t) \leq \mathrm{SOC}_s(t)^{max} \qquad \forall t \tag{3-36}$$

$$P_{pv}(\mathrm{t}) = P_{pv.ds}(\mathrm{t}) + P_{s.\mathrm{pv}char}(t) \qquad \forall pv, \forall s, \forall t \tag{3-37}$$

$$P_{pv}^{min}(t) \leq P_{pv}(\mathrm{t}) \leq Percent.sun(t) * P_{pv}^{max}(t) \qquad \forall pv, \forall t \tag{3-38}$$

$$P_{pv.ds}(\mathrm{t}) \leq \sum_{i=1}^{I} P_i u_i(t) \qquad \forall i, \forall pv, \forall t \tag{3-39}$$

$$u_i(t) \in [0,1] \qquad \forall \mathrm{i}, \forall \mathrm{t} \tag{3-40}$$

$$u_{i.ini}(t=0) = \begin{cases} 0 & t_{ON.ini} \leq 0 \\ 1 & t_{ON.ini} > 0 \end{cases} \qquad \forall i, \forall t \tag{3-41}$$

$$u_{s.char}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \tag{3-42}$$

$$u_{s.dischar}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \tag{3-43}$$

$$u_{s.char}(t) + u_{s.dischar}(t) = 1 \qquad \forall s, \forall t \qquad (3\text{-}44)$$

The aim of House C is to minimise the cost of energy bills. Since the capacities of PV panels considered in residential houses are typically smaller than 5MW, Feed-In Tariff (FIT) is considered as the financial support to the homeowners in the UK. A detailed introduction of FIT tariff can be found in section 3.2.4. FIT has 'generation tariff' and 'export tariff'. In House C, the owner receives income from 'generation tariff' $\pi_{FIT.gen}(t)$ (as part of the FIT) because of PV energy production. Therefore, the energy bill cost in equation (3-26) considers the income benefited from the PV energy generation $P_{pv}(t)$.

The energy generated by the PV panels $P_{pv}(\mathrm{t})$ can be directly consumed by the home appliances $P_{pv.ds}(\mathrm{t})$ and be stored in the energy storage $P_{s.\mathrm{pv}char}(t)$, as illustrated in Figure 3-5 and specified in equation (3-37). In addition to the home appliances consumption, the total consumption of the household in equation(3-27) also considers the charging and discharging activities of the energy storage and the PV supply. Similar to House A and B, the limitations of total consumption allowance is defined in equation (3-28). Moreover, the minimum operating durations of each home appliance, the maximum off durations, and the total running time limit are stated in equation (3-29), (3-30), and (3-32), respectively. As indicated in Figure 3-5, the charging activity of the energy storage charges from the grid supply and the PV energy, which is considered in equation (3-33). SOC level of the energy storage is associated with charging and discharging activities of the energy storage and previous SOC status in equation (3-35). Boundaries of the charging power, discharging power, and SOC levels are enforced in (3-33), (3-34), and (3-36). The total generated PV power at each time slot does not exceed the power that the PV panels could generate $P_{pv}^{max}(t)$ from the sun radiation $Percent.sun(t)$ in (3-38). In addition, equation (3-39) ensures the energy that PV supplies the home appliances not exceed the energy consumed by themselves. In a similar manner as House B, binary numbers are defined in equation (3-40) and (3-41) to indicate the on/off and initial status of each home appliances. Equation (3-42) and (3-43) use binary numbers to determine the charging and discharging activity of the energy storage. Since the storage charging and discharging activity cannot occur at the same time, equation (3-44) enforces the limitation.

3.2.3.4. House D

The same as House C, House D has seven home appliances, one energy storage and PV panels. The PV energy can not only be consumed inside House D, but also can be exported back to the grid. Moreover, the energy storage can also export its energy to the network to earn payments, as illustrated in Figure 3-6.

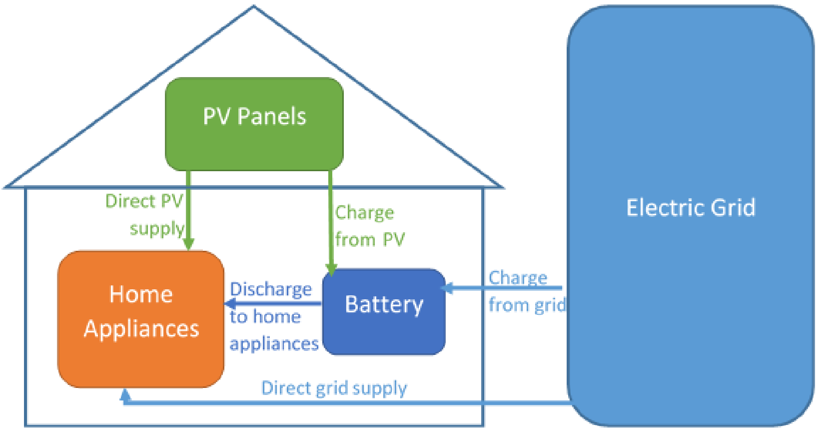


Figure 3-5 Illustration of Energy Flows in House C

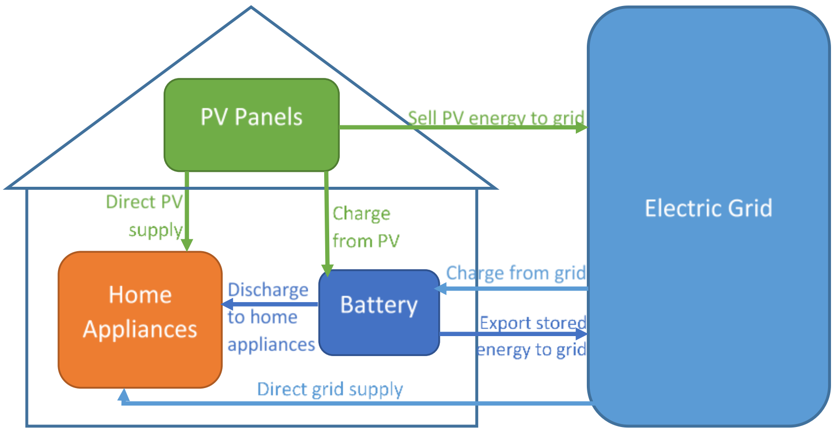


Figure 3-6 Illustration of Energy Flows in House D

Objective function:

$$\underset{t}{Minimise}\,COST = \sum_{t=1}^{T} \left\{ \begin{array}{c} P(t) * \pi(t) - P_{pv}(t) * \pi_{FIT.gen}(t) \\ -P_{pv.exp}(\mathrm{t}) * \pi_{FIT.exp}(t) - P_{s.\mathrm{exp}}(t) * \pi_{s.exp}(t) \end{array} \right\}$$

(3-45)

Subject to**:**

$$P(t) = \left\{\sum_{i=1}^{I} P_i u_i(t)\right\} + P_{s.char.grid}(t) - P_{s.dischar.app}(t) - P_{pv.ds}(\mathrm{t})$$

$$\forall i, \forall s, \forall pv, \forall t \in T \quad (3\text{-}46)$$

$$P_{min}(t) \leq P(t) \leq P_{max}(t) \qquad \forall t \quad (3\text{-}47)$$

$$T_{i.\ ON} \geq \begin{cases} T_{i.\ op} \\ T_{i.\ op} - t_{ON.ini} & if\ u_{i.ini}(t=0) = 1 \end{cases} \qquad \forall i, \forall t \quad (3\text{-}48)$$

$$T_{i.\ OFF} \leq \begin{cases} T_{i.\ off}^{max} \\ T_{i.\ off}^{max} + t_{ON.ini} & if\ u_{i.ini}(t=0) = 0 \end{cases} \qquad \forall i, \forall t \quad (3\text{-}49)$$

$$U_{i\ ON} = 1^T * u_i(t) \qquad \forall i, \forall t \quad (3\text{-}50)$$

$$U_{i\ ON}^{min} \leq U_{i\ ON} \leq U_{i\ ON}^{max} \qquad \forall i \quad (3\text{-}51)$$

$$u_{s.char}(t) * P_{s.char}^{min}(t) \leq P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t)$$

$$\leq u_{s.char}(t) * P_{s.char}^{max}(t) \quad \forall s, \forall t \quad (3\text{-}52)$$

$$u_{s.dischar}(t) * P_{s.dischar}^{min}(t) \leq P_{s.dischar.app}(t) + P_{s.\exp}(t)$$

$$\leq u_{s.dischar}(t) * P_{s.dischar}^{max}(t) \quad \forall s, \forall t \quad (3\text{-}53)$$

$$\mathrm{SOC}_s(t) = \mathrm{SOC}_s(t-1) + P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t)$$

$$-P_{s.dischar.app}(t) - P_{s.\exp}(t) \quad \forall \mathrm{s}, \forall \mathrm{t} \quad (3\text{-}54)$$

$$\mathrm{SOC}_s(t)^{min} \leq \mathrm{SOC}_s(t) \leq \mathrm{SOC}_s(t)^{max} \qquad \forall t \quad (3\text{-}55)$$

$$P_{pv}(\mathrm{t}) = P_{pv.ds}(\mathrm{t}) + P_{s.\mathrm{pv}char}(t) + P_{pv.exp}(\mathrm{t}) \qquad \forall pv, \forall s, \forall t \quad (3\text{-}56)$$

$$P_{pv}^{min}(t) \leq P_{pv}(\mathrm{t}) \leq Percent.sun(t) * P_{pv}^{max}(t) \qquad \forall pv, \forall t \quad (3\text{-}57)$$

$$P_{pv.ds}(\mathrm{t}) + P_{s.dischar.app}(t) \leq \sum_{i=1}^{I} P_i u_i(t) \quad \forall i, \forall pv, \forall t \tag{3-58}$$

$$u_i(t) \in [0,1] \qquad \forall \mathrm{i}, \forall \mathrm{t} \tag{3-59}$$

$$u_{i.ini}(t=0) = \begin{cases} 0 & t_{ON.ini} \leq 0 \\ 1 & t_{ON.ini} > 0 \end{cases} \qquad \forall i, \forall t \tag{3-63}$$

$$u_{s.char}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \tag{3-64}$$

$$u_{s.dischar}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \tag{3-65}$$

$$u_{s.char}(t) + u_{s.dischar}(t) = 1 \qquad \forall s, \forall t \tag{3-66}$$

In House D, the energy generated by PV panels can be consumed inside the house and/or be sold into the grid. The FIT tariff includes ‘generation tariff’ and ‘export tariff’, where ‘generation tariff’ pays for the amount of PV energy generated and ‘export tariff’ pays for the amount of PV energy exported to the grid. As illustrated in Figure 3-6, the PV panels can supply the home appliances directly $P_{pv.ds}(\mathrm{t})$, and/or sell the energy $P_{pv.exp}(\mathrm{t})$ to the grid. In addition to supplying and/or selling energy directly, the energy produced by the PV panels can be stored into the energy storage. Moreover, the energy stored in the storage device can be discharged and sold to the grid. Thus, the energy bills cost considers the FIT tariff savings and energy storage exportation payments, and the objective of House D is to minimise the bill cost (equation (3-45)).

The energy consumption of House D is defined in equation (3-46) with its limitations enforced in (3-47), which involves the PV energy supply $P_{pv.ds}(\mathrm{t})$ and the storage device supply $P_{s.dischar.app}(t)$ to home appliances. Similar to the houses in the above sections, the home appliances have several constraints, including the minimum operating durations of each home appliance (3-48), the maximum off duration (3-49), and the total running time periods limit (3-51). As defined in equation (3-52), the energy storage can be used to store the energy generated by PV $P_{s.\mathrm{pv}char}(t)$and can also charge from the grid $P_{s.char.grid}(t)$. Furthermore, the battery can discharge to supply home appliances $P_{s.dischar.app}(t)$ and sell the stored energy to the grid $P_{s.\exp}(t)$, which is given in equation (3-53). The SOC of the battery, as defined in equation (3-54), is related to the charging and discharging activities of the battery and previous SOC status. As mentioned above, the PV panels can directly supply the home appliances $P_{pv.ds}(\mathrm{t})$ and/or sell its energy $P_{pv.exp}(\mathrm{t})$, and the PV energy could be stored in the battery $P_{s.\mathrm{pv}char}(t)$ to be used later. This is formulated in equation (3-56). The limitation of the amount of energy that PV can produce is defined in (3-57). In equation (3-58), it enforces the supply from the PV and the energy storage to home appliances should not exceed the amount of energy consumed by the appliances themselves. Binary numbers defined in equation (3-59), (3-63), (3-64) and (3-65) represent the on/off and initial statuses of the home appliances, the charging and discharging status of the energy storage, respectively. The constraint (3-66) limits the charging and discharging activity cannot occur at the same time for the energy storage.

3.2.3.5. House E

House E has an additional EV connected to the house when compared to House D. It has seven home appliances, an energy storage device, PV panels, and an EV. The same as House D, the PV production and the energy storage device are both able to export back to the grid and earn payments. The EV in House E needs to be charged to a pre-defined target SOC level before/at the time when it is needed, so that it is ready to drive away. Later in the day, the EV will return to House E with its remaining energy stored in the EV battery. When it returns to the house, it will be plugged into the house and its charging activity will be scheduled. In this way, the EV will be ready to drive the next morning (at the target SOC level).

Objective function:

$$\underset{t}{Minimise}\, COST = \sum_{t=1}^{T} \left\{ \begin{array}{c} P(t) * \pi(t) - P_{pv}(t) * \pi_{FIT.gen}(t) \\ -P_{pv.exp}(\mathrm{t}) * \pi_{FIT.exp}(t) - P_{s.\exp}(t) * \pi_{s.exp}(t) \end{array} \right\}$$

(3-67)

Subject to**:**

$$P(t) = \left\{\sum_{i=1}^{I} P_i u_i(t)\right\} + P_{s.char.grid}(t) - P_{s.dischar.app}(t) - P_{pv.ds}(\mathrm{t})$$

$$+ P_{ev.char.grid}(t) \quad \forall i, \forall s, \forall pv, \forall ev, \forall t \in \{1, \dots, T\} \tag{3-68}$$

$$P_{min}(t) \leq P(t) \leq P_{max}(t) \qquad \forall t \tag{3-69}$$

$$T_{i.\ ON} \geq \begin{cases} T_{i.\ op} & \\ T_{i.\ op} - t_{ON.ini} & if\ u_{i.ini}(t=0) = 1 \end{cases} \qquad \forall i, \forall t \tag{3-70}$$

$$T_{i.\ OFF} \leq \begin{cases} T_{i.\ off}^{max} & \\ T_{i.\ off}^{max} + t_{ON.ini} & if\ u_{i.ini}(t=0) = 0 \end{cases} \qquad \forall i, \forall t \tag{3-71}$$

$$U_{i\ ON} = 1^T * u_i(t) \qquad \forall i, \forall t \tag{3-72}$$

$$U_{i\ ON}^{min} \leq U_{i\ ON} \leq U_{i\ ON}^{max} \qquad \forall i \tag{3-73}$$

$$u_{s.char}(t) * P_{s.char}^{min}(t) \leq P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t)$$

$$\leq u_{s.char}(t) * P_{s.char}^{max}(t) \quad \forall s, \forall t \tag{3-74}$$

$$u_{s.dischar}(t) * P_{s.dischar}^{min}(t) \leq P_{s.dischar.app}(t) + P_{s.\mathrm{exp}}(t) + P_{s.dischar.ev}(t)$$

$$\leq u_{s.dischar}(t) * P_{s.dischar}^{max}(t) \quad \forall s, \forall t \tag{3-75}$$

$$\mathrm{SOC}_s(t) = SOC_s(t-1) + P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t) - P_{s.dischar.app}(t)$$

$$-P_{s.\mathrm{exp}}(t) - P_{s.dischar.ev}(t) \quad \forall \mathrm{s}, \forall \mathrm{t} \tag{3-76}$$

$$SOC_s(t)^{min} \leq \mathrm{SOC}_s(t) \leq SOC_s(t)^{max} \qquad \forall \mathrm{s}, \forall t \tag{3-77}$$

$$P_{pv}(\mathrm{t}) = P_{pv.ds}(\mathrm{t}) + P_{s.\mathrm{pv}char}(t) + P_{pv.exp}(\mathrm{t}) + P_{pv.ev}(\mathrm{t}) \quad \forall pv, \forall s, \forall t \tag{3-78}$$

$$P_{pv}^{min}(t) \leq P_{pv}(\mathrm{t}) \leq Percent.sun(t) * P_{pv}^{max}(t) \qquad \forall pv, \forall t \tag{3-79}$$

$$P_{pv.ds}(\mathrm{t}) + P_{s.dischar.app}(t) \leq \sum_{i=1}^{I} P_i u_i(t) \quad \forall i, \forall pv, \forall t \qquad (3\text{-}80)$$

$$u_{ev.char}(t_1) * P_{ev.char}^{min}(t) \leq P_{ev.char.grid}(t) + P_{s.dischar.ev}(t) + P_{pv.ev}(\mathrm{t})$$

$$\leq u_{ev.char}(t_1) * P_{ev.char}^{max}(t)$$

$$\forall s, \forall pv, \forall ev, \forall t_1 \in \{1, \dots, T\} \quad (3\text{-}81)$$

$$\mathrm{SOC}_{ev}(t) = SOC_{ev}(t-1) + P_{ev.char.grid}(t) + P_{s.\mathrm{dischar}.ev}(t) + P_{pv.ev}(t)$$

$$\forall \mathrm{s}, \forall pv, \forall ev, \forall \mathrm{t} \quad (3\text{-}82)$$

$$SOC_{ev}(t)^{min} \leq \mathrm{SOC}_{ev}(t) \leq SOC_{ev}(t)^{max} \qquad \forall \mathrm{ev}, \forall t \qquad (3\text{-}83)$$

$$\mathrm{SOC}_{ev}\left(t_{ev.target}\right) \geq \mathrm{SOC}_{ev.target} \qquad \forall \mathrm{ev}, \forall t_{ev.target} \in \{1, \dots, T\} \quad (3\text{-}84)$$

$$u_i(t) \in [0,1] \qquad \forall \mathrm{i}, \forall \mathrm{t} \qquad (3\text{-}85)$$

$$u_{i.ini}(t=0) = \begin{cases} 0 & t_{ON.ini} \leq 0 \\ 1 & t_{ON.ini} > 0 \end{cases} \qquad \forall i, \forall t \qquad (3\text{-}86)$$

$$u_{s.char}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \qquad (3\text{-}87)$$

$$u_{s.dischar}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \qquad (3\text{-}88)$$

$$u_{s.char}(t) + u_{s.dischar}(t) = 1 \qquad \forall s, \forall t \qquad (3\text{-}89)$$

$$u_{ev.char}(t_1) \begin{cases} \in [0,1] & \forall t_1 \in t_{ev.char} \\ = 0 & \forall t_1 \notin t_{ev.char} \end{cases}$$

$$\forall t_{ev.char} \in \{1, \dots, t_{ev.target}, t_{ev.return}, \dots, T\} \quad (3\text{-}90)$$

The objective of House E is to minimise the energy bill cost, which is defined in equation (3-67). The energy bill cost is related to the cost of household consumption and earnings of exporting energy from PV and energy storage. The household consumption is defined in equation(3-68), which considers the home appliances consumption, the energy used to charge the energy storage $P_{s.char.grid}(t)$ and the EV $P_{ev.char.grid}(t)$, and the energy supplied by the energy storage $P_{s.dischar.app}(t)$ and the PV $P_{pv.ds}(\mathrm{t})$. Furthermore, the consumption allowance of House E is enforced in equation (3-69).

For the home appliances, their minimum running time, maximum off time, and total running time are calculated and limited in equation (3-70), (3-71), (3-72) and (3-73), respectively. The energy storage can charge from both grid supply and PV energy production. Energy stored in the storage can discharge to supply the home appliances $P_{s.dischar.app}(t)$ and the EV $P_{s.dischar.ev}(t)$, and it can also export its stored energy $P_{s.\mathrm{exp}}(t)$ back to the grid. The charging and discharging power are limited in equation (3-74) and (3-75). The energy stored in the energy storage (i.e. SOC) is associated with its charging and discharging activities and previous SOC status. The SOC status is computed in equation (3-76) together with the capacity of the energy storage limited in equation(3-77).

As determined in equation (3-78), the PV supplies the home appliances $P_{pv.ds}(\mathrm{t})$, the storage $P_{s.\mathrm{pv}char}(t)$ and the EV $P_{pv.ev}(\mathrm{t})$, and it can also deliver energy back to the grid $P_{pv.exp}(\mathrm{t})$ at the same time. The maximum PV production is linked to solar radiation in equation (3-79). Moreover, it is enforced in equation (3-80) that the energy supplied from the PV and the energy storage to the home appliances should not exceed the amount of energy consumed by the appliances themselves. The EV can charge from the grid supply $P_{ev.char.grid}(t)$, the energy storage $P_{s.dischar.ev}(t)$ and the PV $P_{pv.ev}(\mathrm{t})$, as defined in equation (3-81). The SOC level $\mathrm{SOC}_{ev}(t)$ stored in the EV battery is calculated based on its charging activity and its previous SOC status $SOC_{ev}(t-1)$ in equation (3-82). The SOC of the EV battery should not exceed its capacity, this is presented as equation (3-83). At the target time $t_{ev.target}$ when the EV needs to be ready to drive away, the energy stored in the EV battery $\mathrm{SOC}_{ev}(t_{ev.target})$ needs to reach the target SOC level $\mathrm{SOC}_{ev.target}$ in equation (3-84).

Binary variables that determine and indicate the on/off and initial status of home appliances are defined in equation (3-85) and (3-86), respectively. In equation (3-87) and (3-88), the binary variables decide the energy storage charging and discharging activities. Since the charging and discharging activity of the energy storage cannot occur at the same time, equation (3-89) introduces the restriction. The charging time and charging behaviour of the EV is determined in equation (3-90). The EV charges from the time it returns to the house $t_{ev.return}$ until the time $t_{ev.target}$ it left the house next morning.

3.2.3.6. House F

House F replaces the space heating in House D with a storage heater. Therefore, House F has six home appliances (electric water heater, washing machine, cooking devices, dishwasher, fridge freezer and TV), a storage heater, an energy storage device, and PV panels. In House F, the energy storage and PV panels can export their surplus energy to the grid to achieve energy savings. The storage heater has a target SOC level to be met at a pre-described time set by customers. Normally, it is when customers return to the house.

Objective function:

$$\underset{t}{Minimise}\, COST = \sum_{t=1}^{T} \left\{ \begin{array}{c} P(t) * \pi(t) - P_{pv}(t) * \pi_{FIT.gen}(t) \\ -P_{pv.exp}(\mathrm{t}) * \pi_{FIT.exp}(t) - P_{s.\mathrm{exp}}(t) * \pi_{s.exp}(t) \end{array} \right\} \tag{3-91}$$

Subject to**:**

$$P(t) = \left\{ \sum_{i=1}^{I} P_i u_i(t) \right\} + P_{s.char.grid}(t) \; - \; P_{s.dischar.app}(t) - P_{pv.ds}(\mathrm{t})$$

$$+P_{sh.char.grid}(t) \quad \forall i, \forall s, \forall pv, \forall sh, \forall t \in \{1, \dots, T\} \tag{3-92}$$

$$P_{min}(t) \leq P(t) \leq \; P_{max}(t) \qquad \forall t \tag{3-93}$$

$$T_{i.\ ON} \geq \begin{cases} T_{i.\ op} & \\ T_{i.\ op} - \; t_{ON.ini} & if\ u_{i.ini}(t=0) = 1 \end{cases} \qquad \forall i, \forall t \tag{3-94}$$

$$T_{i.\ OFF} \le \begin{cases} T_{i.\ off}^{max} \\ T_{i.\ off}^{max} + t_{ON.ini} \quad if\ u_{i.ini}(t=0)=0 \end{cases} \qquad \forall i, \forall t \qquad (3\text{-}95)$$

$$U_{i\ ON} = 1^T * u_i(t) \qquad \forall i, \forall t \qquad (3\text{-}96)$$

$$U_{i\ ON}^{min} \le U_{i\ ON} \le U_{i\ ON}^{max} \qquad \forall i \qquad (3\text{-}97)$$

$$u_{s.char}(t) * P_{s.char}^{min}(t) \le P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t) \le u_{s.char}(t) * P_{s.char}^{max}(t) \quad \forall s, \forall t (3\text{-}98)$$

$$u_{s.dischar}(t) * P_{s.dischar}^{min}(t) \le P_{s.dischar.app}(t) + P_{s.\exp}(t) + P_{s.dischar.sh}(t) \le u_{s.dischar}(t) * P_{s.dischar}^{max}(t) \quad \forall s, \forall t (3\text{-}99)$$

$$\mathrm{SOC}_s(t) = SOC_s(t-1) + P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t) - P_{s.dischar.app}(t) - P_{s.\exp}(t) - P_{s.dischar.sh}(t) \quad \forall \mathrm{s}, \forall \mathrm{t} (3\text{-}100)$$

$$SOC_s(t)^{min} \le \mathrm{SOC}_s(t) \le SOC_s(t)^{max} \qquad \forall \mathrm{s}, \forall t \qquad (3\text{-}101)$$

$$P_{pv}(\mathrm{t}) = P_{pv.ds}(\mathrm{t}) + P_{s.\mathrm{pv}char}(t) + P_{pv.exp}(\mathrm{t}) + P_{pv.sh}(\mathrm{t}) \qquad \forall pv, \forall s, \forall t\ (3\text{-}102)$$

$$P_{pv}^{min}(t) \le P_{pv}(\mathrm{t}) \le Percent.sun(t) * P_{pv}^{max}(t) \qquad \forall pv, \forall t \qquad (3\text{-}103)$$

$$P_{pv.ds}(\mathrm{t}) + P_{s.dischar.app}(t) \le \sum_{i=1}^{I} P_i u_i(t) \quad \forall i, \forall pv, \forall t \qquad (3\text{-}104)$$

$$u_{sh.char}(t) * P_{sh.char}^{min}(t) \le P_{sh.char.grid}(t) + P_{s.dischar.sh}(t) + P_{pv.sh}(\mathrm{t}) \le u_{sh.char}(t) * P_{sh.char}^{max}(t) \quad \forall s, \forall pv, \forall sh, \forall t\ (3\text{-}105)$$

$$\mathrm{SOC}_{sh}(t) = SOC_{sh}(t-1) + P_{sh.char.grid}(t) + P_{s.\mathrm{dischar}.sh}(t) + P_{pv.sh}(t) - P_{sh.\mathrm{dischar}}(t) \qquad \forall \mathrm{s}, \forall pv, \forall sh, \forall \mathrm{t} \qquad (3\text{-}106)$$

$$SOC_{sh}(t)^{min} \le \mathrm{SOC}_{sh}(t) \le SOC_{sh}(t)^{max} \qquad \forall \mathrm{sh}, \forall t \qquad (3\text{-}107)$$

$$\mathrm{SOC}_{sh}\left(t_{sh.target}\right) \geq \mathrm{SOC}_{sh.target} \qquad \forall \mathrm{sh}, \forall t_{sh.target} \in \{1, \dots, T\} \quad (3\text{-}108)$$

$$u_i(t) \in [0,1] \qquad \forall \mathrm{i}, \forall \mathrm{t} \quad (3\text{-}109)$$

$$u_{i.ini}(t=0) = \begin{cases} 0 & t_{ON.ini} \leq 0 \\ 1 & t_{ON.ini} > 0 \end{cases} \qquad \forall i, \forall t \quad (3\text{-}110)$$

$$u_{s.char}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \quad (3\text{-}111)$$

$$u_{s.dischar}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \quad (3\text{-}112)$$

$$u_{s.char}(t) + u_{s.dischar}(t) = 1 \qquad \forall s, \forall t \quad (3\text{-}113)$$

$$u_{sh.char}(t) \in [0,1] \qquad \forall \mathrm{sh}, \forall \mathrm{t} \quad (3\text{-}114)$$

The aim of scheduling House F is to minimise its energy bill payment, which is linked to the household consumption and the energy exported by the storage $P_{s.\exp}(t)$ and the PV $P_{pv.exp}(\mathrm{t})$ in equation (3-91). The household consumption in equation (3-92) is computed based on the energy consumed by the home appliances, the energy storage $P_{s.char.grid}(t)$ and the storage heater $P_{sh.char.grid}(t)$, and the energy supplied by the energy storage $P_{s.dischar.app}(t)$ and the PV $P_{pv.ds}(\mathrm{t})$ to the home appliances within House F. The allowance of the household consumption is restricted in equation (3-93).

The minimum running time, maximum off time and total running time of home appliances are calculated and limited in equation (3-94) to (3-97). The energy storage can charge from the grid and the PV, and discharge to supply the appliances, the storage heater $P_{s.dischar.sh}(t)$ and to export energy back to the grid in equation (3-98) and (3-99). Thus, the energy stored in the energy storage is related to the charging and discharging activities and its previous SOC status in equation (3-100). The capacity of the energy storage is defined in equation (3-101). The PV can supply the home appliances, the storage heater $P_{pv.sh}(\mathrm{t})$ and the energy storage. It can also export energy to the grid to earn exportation payments in equation (3-102). It is enforced in equation (3-104) that the energy supplied from the PV and the energy storage to the home devices should not exceed the energy consumed by the devices. The storage heater can charge its heat energy from the grid supply $P_{sh.char.grid}(t)$, the energy storage $P_{s.dischar.sh}(t)$ and the PV $P_{pv.sh}(\mathrm{t})$ in equation (3-105). The heat level stored in the storage heater $\mathrm{SOC}_{sh}(t)$is computed based on its charging activity in equation (3-106). In addition, if there is heat stored in the storage heater, it has a heat dispensing rate $P_{sh.\mathrm{dischar}}(t)$, which is also included in equation (3-106). The capacity of the storage heater is defined in equation (3-107). By the target time $t_{sh.target}$, the heat stored in the storage heater $\mathrm{SOC}_{sh}(t_{sh.target})$ needs to reach the level $\mathrm{SOC}_{sh.target}$ pre-defined by the customer in equation (3-108).

Binary variables in equation (3-109) to (3-112) and (3-114) decide the on/off and initial status of the home appliances, the charging and discharging activities of the energy storage and the charging behaviour of the storage heater $u_{sh.char}(t)$, respectively. As the energy storage cannot charge and discharge at the same time, this is limited in equation (3-113).

3.2.3.7. House G

House G is a combination of House E and House F. It has six home appliances, one storage heater, one EV, one energy storage device, and PV panels. In the same manner, the energy storage and PV panels can export their energy back to the grid.

Objective function:

$$\underset{t}{Minimise}\, COST = \sum_{t=1}^{T} \begin{Bmatrix} P(t) * \pi(t) - P_{pv}(t) * \pi_{FIT.gen}(t) \\ -P_{pv.exp}(\mathrm{t}) * \pi_{FIT.exp}(t) - P_{s.\mathrm{exp}}(t) * \pi_{s.exp}(t) \end{Bmatrix}$$

(3-115)

Subject to**:**

$$P(t) = \{\textstyle\sum_{i=1}^{I} P_i u_i(t)\} + P_{s.char.grid}(t) - P_{s.dischar.app}(t) - P_{pv.ds}(\mathrm{t}) + P_{ev.char.grid}(t) + P_{sh.char.grid}(t) \quad \forall i, \forall s, \forall pv, \forall ev, \forall sh, \forall t \in \{1, \ldots, T\}$$

(3-116)

$$P_{min}(t) \leq P(t) \leq P_{max}(t) \qquad \forall t \tag{3-117}$$

$$T_{i.\ ON} \geq \begin{cases} T_{i.\ op} \\ T_{i.\ op} - t_{ON.ini} & if\ u_{i.ini}(t=0)=1 \end{cases} \qquad \forall i, \forall t \tag{3-118}$$

$$T_{i.\ OFF} \leq \begin{cases} T_{i.\ off}^{max} \\ T_{i.\ off}^{max} + t_{ON.ini} & if\ u_{i.ini}(t=0)=0 \end{cases} \qquad \forall i, \forall t \tag{3-119}$$

$$U_{i\ ON} = 1^T * u_i(t) \qquad \forall i, \forall t \tag{3-120}$$

$$U_{i\ ON}^{min} \leq U_{i\ ON} \leq U_{i\ ON}^{max} \qquad \forall i \tag{3-121}$$

$$u_{s.char}(t) * P_{s.char}^{min}(t) \leq P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t) \leq u_{s.char}(t) * P_{s.char}^{max}(t) \qquad \forall s, \forall t \tag{3-122}$$

$$u_{s.dischar}(t) * P_{s.dischar}^{min}(t) \leq P_{s.dischar.app}(t) + P_{s.\mathrm{exp}}(t) + P_{s.dischar.ev}(t) + P_{s.dischar.sh}(t) \leq u_{s.dischar}(t) * P_{s.dischar}^{max}(t) \qquad \forall s, \forall t \tag{3-123}$$

$$\mathrm{SOC}_s(t) = SOC_s(t-1) + P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t) - P_{s.dischar.app}(t) - P_{s.\mathrm{exp}}(t) - P_{s.dischar.ev}(t) - P_{s.dischar.sh}(t) \qquad \forall \mathrm{s}, \forall \mathrm{t} \tag{3-124}$$

$$SOC_s(t)^{min} \leq \mathrm{SOC}_s(t) \leq SOC_s(t)^{max} \qquad \forall \mathrm{s}, \forall t \tag{3-125}$$

$$P_{pv}(\mathrm{t}) = P_{pv.ds}(\mathrm{t}) + P_{s.\mathrm{pv}char}(t) + P_{pv.exp}(\mathrm{t}) + P_{pv.ev}(\mathrm{t}) + P_{pv.sh}(\mathrm{t}) \qquad \forall pv, \forall s, \forall t \tag{3-126}$$

$$P_{pv}^{min}(t) \leq P_{pv}(\mathrm{t}) \leq Percent.sun(t) * P_{pv}^{max}(t) \qquad \forall pv, \forall t \tag{3-127}$$

$$P_{pv.ds}(\mathrm{t}) + P_{s.dischar.app}(t) \leq \sum_{i=1}^{I} P_i u_i(t) \qquad \forall i, \forall pv, \forall \mathrm{s}, \forall t \tag{3-128}$$

$$u_{ev.char}(t_1) * P_{ev.char}^{min}(t) \leq P_{ev.char.grid}(t) + P_{s.dischar.ev}(t) + P_{pv.ev}(\mathrm{t})$$

$$\leq u_{ev.char}(t_1) * P_{ev.char}^{max}(t)$$

$$\forall s, \forall pv, \forall ev, \forall t_1 \in \{1, \dots, T\}, \forall t \quad (3\text{-}129)$$

$$\mathrm{SOC}_{ev}(t) = SOC_{ev}(t-1) + P_{ev.char.grid}(t) + P_{s.\mathrm{dischar}.ev}(t) + P_{pv.ev}(t)$$

$$\forall \mathrm{s}, \forall pv, \forall ev, \forall \mathrm{t} \quad (3\text{-}130)$$

$$SOC_{ev}(t)^{min} \leq \mathrm{SOC}_{ev}(t) \leq SOC_{ev}(t)^{max} \qquad \forall \mathrm{ev}, \forall t \quad (3\text{-}131)$$

$$\mathrm{SOC}_{ev}(t_{ev.target}) \geq \mathrm{SOC}_{ev.target} \quad \forall \mathrm{ev}, \forall t_{ev.target} \in \{1, \dots, T\} \quad (3\text{-}132)$$

$$u_{sh.char}(t) * P_{sh.char}^{min}(t) \leq P_{sh.char.grid}(t) + P_{s.dischar.sh}(t) + P_{pv.sh}(\mathrm{t})$$

$$\leq u_{sh.char}(t) * P_{sh.char}^{max}(t)$$

$$\forall s, \forall pv, \forall sh, \forall t \quad (3\text{-}133)$$

$$\mathrm{SOC}_{sh}(t) = SOC_{sh}(t-1) + P_{sh.char.grid}(t) + P_{s.\mathrm{dischar}.sh}(t) + P_{pv.sh}(t) -$$

$$P_{sh.\mathrm{dischar}}(t) \qquad \forall \mathrm{s}, \forall pv, \forall sh, \forall \mathrm{t} \quad (3\text{-}134)$$

$$SOC_{sh}(t)^{min} \leq \mathrm{SOC}_{sh}(t) \leq SOC_{sh}(t)^{max} \qquad \forall \mathrm{sh}, \forall t \quad (3\text{-}135)$$

$$\mathrm{SOC}_{sh}(t_{sh.target}) \geq \mathrm{SOC}_{sh.target} \qquad \forall \mathrm{sh}, \forall t_{sh.target} \in \{1, \dots, T\} \quad (3\text{-}136)$$

$$u_i(t) \in [0,1] \qquad \forall \mathrm{i}, \forall \mathrm{t} \quad (3\text{-}137)$$

$$u_{i.ini}(t=0) = \begin{cases} 0 & t_{ON.ini} \leq 0 \\ 1 & t_{ON.ini} > 0 \end{cases} \qquad \forall i, \forall t \quad (3\text{-}138)$$

$$u_{s.char}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \quad (3\text{-}139)$$

$$u_{s.dischar}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \quad (3\text{-}140)$$

$$u_{s.char}(t) + u_{s.dischar}(t) = 1 \qquad \forall s, \forall t \quad (3\text{-}141)$$

$$u_{ev.char}(t_1)\begin{cases} \in [0,1] & \forall t_1 \in t_{ev.char} \\ = 0 & \forall t_1 \notin t_{ev.char} \end{cases}$$

$$\forall ev, \forall t_{ev.char} \in \{1, \dots, t_{ev.target}, t_{ev.return}, \dots, T\} \quad (3\text{-}142)$$

$$u_{sh.char}(t) \in [0,1] \qquad \forall \text{sh}, \forall \text{t} \qquad (3\text{-}143)$$

The objective of House G is to minimise the payment of energy bill during the scheduling time. The energy bill payment is associated with the cost of household consumption and the earnings of exporting energy from the energy storage and the PV, as defined in equation (3-115). The household consumption is calculated in equation (3-116), together with the consumption allowance limited in equation (3-117). The usage preferences of home appliances are enforced in equation (3-118) to (3-121), which are minimum operating time, maximum off time and total running duration. The energy storage can charge from the grid supply and the PV energy in equation (3-122). It can discharge to supply the home appliances, the storage heater and the EV in equation (3-123). Moreover, it can also export its stored energy back to the grid. The SOC level of the energy storage is linked to its charging and discharging activities in equation (3-124). The capacity of the energy storage is defined in equation (3-125).

The PV energy can supply the home devices, the storage heater, the EV and the energy storage. Similar to the energy storage, the PV can also export its energy to the grid. The calculation of the PV energy and its limitation are shown in equation (3-126) and (3-127). In equation (3-128), it is limited that the energy supplied from the energy storage and the PV to the appliances should not exceed the amount of energy consumed by the appliances at any time. The EV and the storage heater can both charge from the grid supply, the PV and the energy storage in equation (3-129) and (3-133). In addition, the storage heater has a constant heat discharge rate when there is heat stored in it. Based on the charging activities and previous SOC status, the energy stored in the EV and in the storage heater is computed in equation (3-130) and (3-134). The capacity of the EV and the storage heater is limited in equation (3-131) and (3-135), respectively. By the target time defined by the customer, the energy stored in the EV and storage heater need to reach its target level in equation (3-132) and (3-136).

The on/off and initial status of the home appliances are indicated by binary variables in equation (3-137) and (3-138). The charging and discharging behaviour of the energy storage are determined by binary variables in equation (3-139) to (3-141), which also restricted that the charging and discharging activities cannot occur at the same time. In equation (3-142) and (3-143), the charging activity of the EV and the storage heater is decided.

Results of the case studies of the scheduling tool are presented in the following section, including the parameters configured for the devices in the case studies.

3.2.4. Case Studies Scheduling Results

The following case studies of the customer-centred scheduling tool in different houses mentioned above employ ToU pricing tariff as an inflow control signal. As stated in section 2.2.3.1.2.1, ToU tariff rates are pre-defined and vary over a day, but the values of the tariff are not associated with the market clearing prices. ToU electricity price tariffs are commonly used in the UK currently, and Economy 7 tariff [55] is a typical example of it. Economy 7 often has discounted rates (normally at 50% of daytime prices) during off-peak periods from late night to early morning. All House types are tested with Economy 7 tariff, in addition, House C-G with PV panels also consider the Feed-In Tariff (FIT) tariff.

For small scale PV systems up to 5MW, FIT is used for specific PV productions in the UK [95]. The FIT scheme was introduced on 1st April 2010, and low carbon electricity generation technologies can participate in the scheme. The FIT contains two payments, which are 'generation tariff' and 'export tariff'. 'Generation tariff' pays for the electricity generated, and 'export tariff' pays for the electricity delivery back to the grid. In addition, customers will receive savings on their energy bills if they use the energy generated by the PV system to supply their own demand. Thus, customers in House C-G will receive additional FIT income.

The ToU and FIT price tariff rates applied will be presented in detail in the case studies results. Configurations of parameters used in the case studies are explained in section 3.2.4.1 below. Following the introduction of parameters, the case study results are presented and discussed. Fico Xpress optimization software [94] is used to solve these optimisation problems.

3.2.4.1. Parameters of Case Studies

The configuration of the following case studies parameters represents one example of the customers' preferences on using home appliances, a small-scale 1kW 10kWh energy storage device, a 40kWh EV, a 3kWh storage heater and a 3kW PV system. All the parameters can be modified in the customer-centred scheduling tool.

The rated consumption of the eight home appliances are referenced from [96] and [97]. Configurations on the values of constraints parameters for each home appliances that applied in the scheduling tool are summarised in Table 3-2.

Table 3-2 Configuration of Home Appliances Parameters

Home Appliances	Initial Status (h) $t_{ON.ini}$	Min Operating Time (h) $T_{i.\ ON}$	Max Off Time (h) $T_{i.\ OFF}$	Running Time (h)	
				Minimum $U_{i\ ON}^{min}$	Maximum $U_{i\ ON}^{max}$
Electric Water Heater	-3	1	18	6	9
Washing Machine	-5	1	23	1	1
Dishwasher	-3	1	23	1	2
Cooking Devices	-4	2	22	2	4
Fridge Freezer[1]	2	24	0	24	24
Space Heating	2	1	19	5	10
TV	-3	1	24	0	3

[1] Fridge Freezer is configured to be constantly on for 24 hours a day in the case studies. However, as the constraints are inputs from customers, they are changeable.

The initial status $t_{ON.ini}$ indicates the initial length of time that the home appliance has been on/off time when the scheduling process starts. For example, the initial status of the electric water heater is -3, which means the water heater has been off for 3 hours. While the initial status of the space heating is 2, this shows the heating has been working for 2 hours before the scheduling begins. The minimum operating, maximum off, minimum and maximum total running time of each home appliances are also given in Table 3-2.

The parameters of the energy storage device are stated in Table 3-3. It is assumed that the initial energy stored in the storage is 1.8kWh, and the amount of energy stored in the battery should not exceed its maximum capacity of 10kWh. Furthermore, charging and discharging power should not exceed the maximum rate (1kW/h). It is configured that the SOC at the end of the scheduling will be the same as the initial SOC stored in the battery when the scheduling starts.

The output profile of PV panels in case studies is referenced from the power output example in Figure 3-7 [98], which gives the output of a 12kW PV system for a week in December from 6 a.m. to 8 p.m. The PV system is configured to have a maximum power output of 3kW, and the PV output uses a similar average percentage as in Figure 3-7. The output of the 3kW PV panels is given in Figure 3-8, and it will apply to House C – G.

Table 3-3 Configurations of Energy Storage Parameters

Energy Storage Device						
Initial SOC (kWh)	Charging Power (kW)		Discharging Power (kW)		SOC_s (kWh)	
	Min	Max	Min	Max	Min	Max
$\mathrm{SOC}_s(0)$	$P_{s.char}^{min}(t)$	$P_{s.char}^{max}(t)$	$P_{s.dischar}^{min}(t)$	$P_{s.dischar}^{max}(t)$	$\mathrm{SOC}_s(t)^{min}$	$\mathrm{SOC}_s(t)^{max}$
1.8	0	1	0	1	0	10

House E and House G both have an EV. It is assumed in the case studies that the EV capacity is 40kWh, which is based on a Nissan Leaf specifications [99]. Moreover, it is specified in [99] that the Nissan Leaf will take 7.5 hours to charge to full capacity.

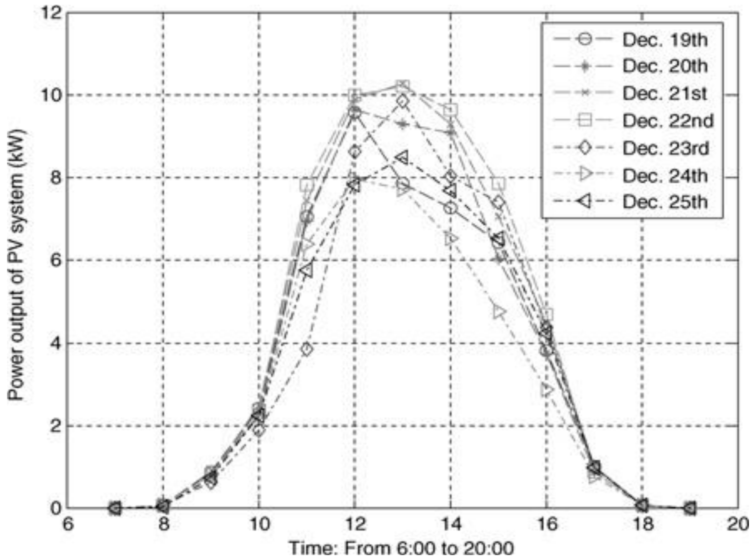


Figure 3-7 One Power Output Example of PV in December [98]

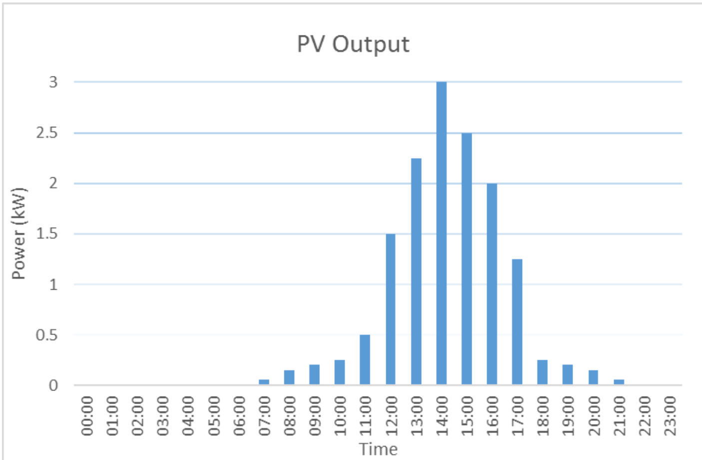


Figure 3-8 PV Output Used in Case Studies

Thus, the maximum charging power of the EV is assumed to be 5kW/h in the case studies. Configurations of the EV parameters are given in Table 3-4. The EV leaves the house at 7 a.m. and returns to the house at 6 p.m. Thus, it is connected to the house for charging from 7 p.m. to 6 a.m. next morning. The EV returns to the house at 6 p.m. with 15kWh energy remained in it. It charges to reach its target SOC level (35 kWh) before it leaves at 7 a.m. the next day. During 7 p.m. to 0 a.m., the EV charges from 15kWh to a predefined level. Then from 1-6a.m., the EV continues to charge from the predefined level to 35kWh. It is presumed in the case studies that the predefined level is 25kWh, which is presented as $SOC(0)$ in Table 3-4.

Table 3-4 Configurations of EV Parameters

Electric Vehicle			
Charging Power (kW)		SOC (kWh)	
Min$P_{ev.char}^{min}(t)$	Max $P_{ev.char}^{max}(t)$	Min$SOC(t)^{min}$	Max$SOC(t)^{max}$
0	5	0	40

SOC of EV at t=0 (kWh) $\mathrm{SOC}(0)$	Time of leaving the house $t_{ev.target}$	Target SOC (kWh) $\mathrm{SOC}_{ev}(t_{ev.target})$	Time of returning to the house $t_{ev.return}$	Remaining SOC when EV returns to the house (kWh) $\mathrm{SOC}_{ev}(t_{ev.return})$
25	7	35	18	15

Furthermore, a storage heater is also considered in case studies (House F and House G). For the houses have the storage heater, the space heating (one of the 7 home appliances) is replaced by it. Detailed configurations of the storage heater are shown in Table 3-5. The storage heater charges (heats) at a maximum rate of 1kW. If there is heat energy stored in the storage heater, it has a heat discharging (dispensing) rate of 0.5kW [100]. The initial SOC (equivalent heat) stored in the storage heater is 3kWh. At 6 p.m., it is expected that the storage heater should have at least 7kWh energy stored in it by the time customer return to the house in the evening. It is also limited that the heat stored in the storage heater will not be lower than the initial SOC stored at any time of the scheduling, to ensure customers' comfort level.

The case studies without EV (House A, House B, House C, House D and House F) have a maximal power supply allowance at 5kW. The cases with EV (House E and House G) have a maximum consumption allowance at 10kW. The power supply allowance of each house is summarised and listed in Table 3-6.

These parameters can be modified according to actively participating consumer's preferences.

Table 3-5 Configurations of Storage Heater Parameters

Storage Heater					
Initial SOC (kWh) $\mathrm{SOC}_{sh}(0)$	Charging Power (kW)		Discharging Power (kW) $P_{sh.\mathrm{dischar}}(t)$	SOC_{sh} (kWh)	
	Min $P^{min}_{sh.char}(t)$	Max $P^{max}_{sh.char}(t)$		Min $\mathrm{SOC}_{sh}(t)^{min}$	Max $\mathrm{SOC}_{sh}(t)^{max}$
3	0	1	0.5	3	10

Table 3-6 Configuration of Power Supply Allowance of Each House

Power supply allowance (kW)						
House A	House B	House C	House D	House E	House F	House G
5	5	5	5	10	5	10

3.2.4.2. Case Study Results of House A

The ToU price scheme used in case studies is based on Economy 7 tariff in the UK, which is shown on the top of Figure 3-9. The price rates are not the real values of Economy 7 tariff[2], they are for illustration purpose only. Economy 7 tariff normally has discounted rates for 7 hours in a day. Thus, from 1 a.m. to 7 a.m. of the ToU price scheme is set as half price of the standard rate during the rest of the day. Grey dots of the price curve in Figure 3-9 shows the illustrative rates of the ToU tariff, the dash line is only used to show the trend of the price curve.

The scheduling results of House A are presented at the bottom of Figure 3-9, and the total consumption at each hour is represented by orange 'x' markers. It can be observed that home appliances are scheduled over the time when the price rates are low (from 1 a.m. to 7 a.m). Fridge and freezer are scheduled not to be switched off over the scheduling period. Cooking devices are regarded as low flexibility home appliances, therefore, the cooking activity has to happen at after-working hours. It is scheduled to operate between 7 and 8 p.m.

[2] The price rates considered in the case studies do not consider network pricin, they are not real price rates used in the UK and only represents the unit rates for each kWh energy used.

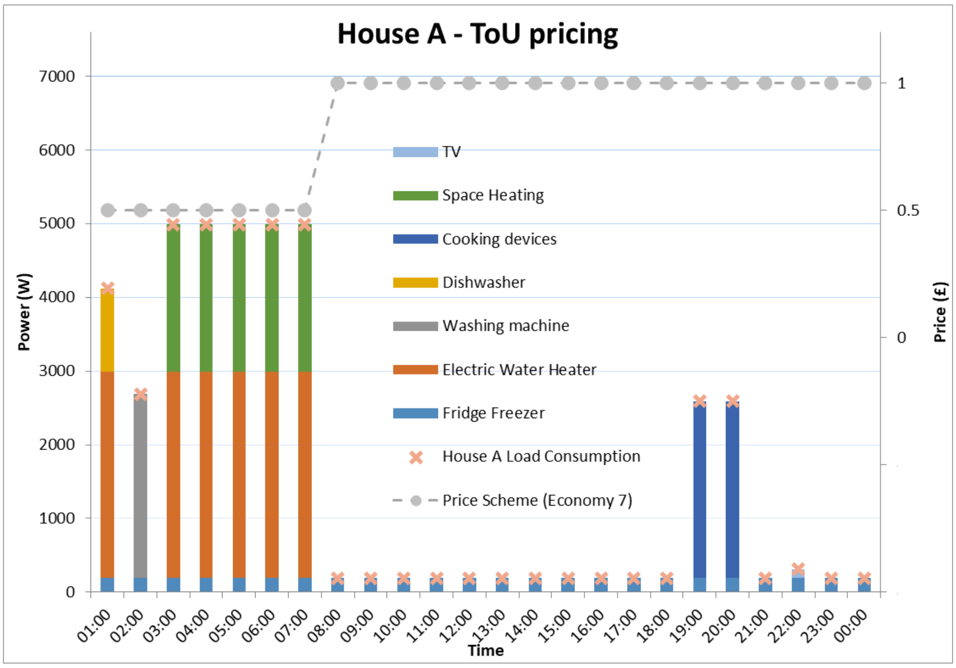


Figure 3-9 Scheduling Results of House A under ToU Tariff

The scheduling tool takes advantage of the low price periods to run large consumption appliances. For those low scheduling flexibility home devices, they have to be used when needed, thus their activities cannot be moved to the low price time period. The energy bill payment of House A is £24.03.

3.2.4.3. Case Study Results of House B

House B has the same 7 home appliances as in House A, and an additional energy storage device.

The scheduling results of House B are given in Figure 3-10. Similar to the scheduling results of House A, the home appliances are scheduled towards the time when price rates are low, i.e. the first 7 hours in the scheduling horizon. The storage device charges to take advantage of the low price time, while it also respects the total consumption limitation, which should not exceed 5kW at any time of the scheduling.

The charging and discharging activities of the energy storage device are also illustrated in Figure 3-11. It charges at 4 a.m. and 7 a.m. when the energy price is at a discounted rate. Furthermore, due to the low scheduling flexibility devices, i.e. cooking devices and TV, have to run during evening time, the energy storage discharges to reduce the consumption when the prices are high at 7 p.m. and 8 p.m. The storage device adds flexibility in the scheduling of home appliances, which discharges during the evening peak of House B at its maximum power and charges when the energy prices are low. It can be observed that the SOC of the storage device (blue markers in Figure 3-11) changes with the charging and discharging activities. The energy stored in the energy storage at the end of the scheduling is enforced to be the same as that at the start. The energy bill payment of House B is £23.03.

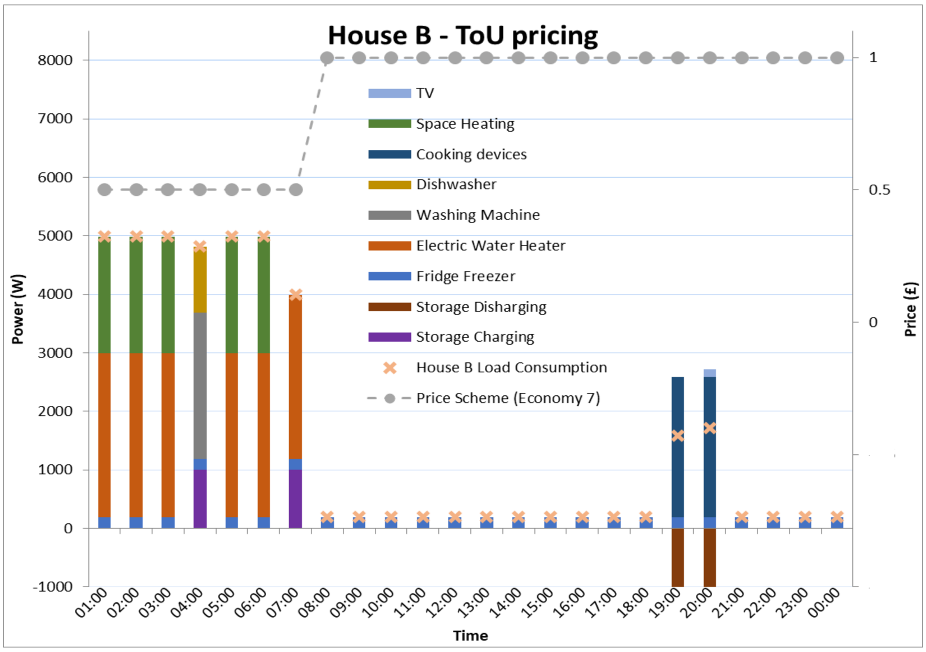


Figure 3-10 Scheduling Results of House B under ToU Tariff

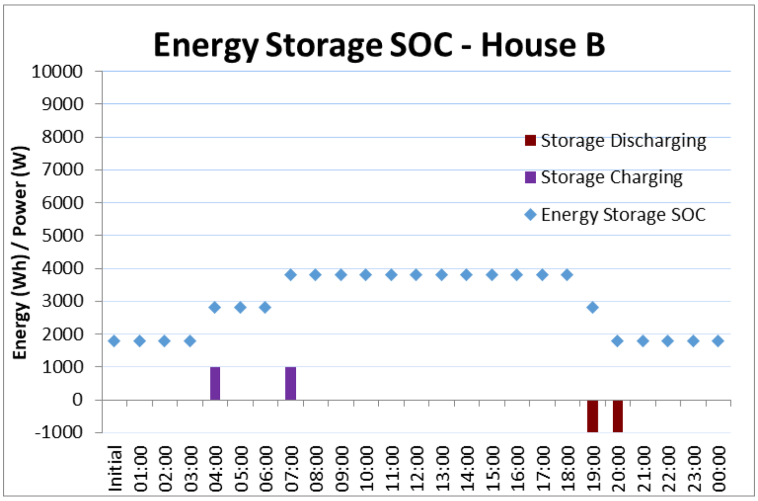


Figure 3-11 Energy Storage Charging and Discharging Activity and its SOC in House B

3.2.4.4. Case Study Results of House C

Since House C has PV panels installed, House C is eligible for receiving FIT payments. The FIT rates published by Ofgem can be found in [101]. Although Economy 7 tariff rates used in the case studies are not the real values applied to residential houses, they show the ratio between the standard price and discounted price used in real energy bills. In a similar manner, the FIT rates mentioned above are processed so to show the ratio between the FIT rates and the standard rates. Note that the price signals sent to House C include Economy 7 tariff and FIT, in which FIT encourages customers in House C to utilise the PV energy. Customers in House C consume PV inside the house and the PV energy is not exported back to the grid. For the amount of energy that the PV panels generated, House C will receive additional income through the ‘generation tariff’ of FIT payments.

The scheduling results of home appliances and energy storage device are presented in Figure 3-12. Since the objective is to achieve minimal energy bill payments, the scheduling tool utilises all the available PV energy production. Therefore, the bill payment of House C (£14.11) is lower than House A (£24.03) and B (£23.03), due to additional FIT payment received. During the first seven hours that has discounted energy price, heavy usage home appliances are scheduled to run a few hours and energy storage charges at the last six hours of discounted rates.

As presented in Figure 3-13, the produced PV energy can be stored into the energy storage and/or be used to supply the home appliances directly. The amount of PV energy that supplies the home appliances directly are shown as light green bars (minus values) in Figure 3-12 and dark green bars (positive values) in Figure 3-13. It can be observed that the majority of the PV production supplies to the appliances in House C. Thus, large consumption home appliances are scheduled to run during the PV production time. In addition, for the evening peak time when the cooking devices are in operation, the scheduling tool schedules the PV and the energy storage to supply the consumption to lower the evening peak.

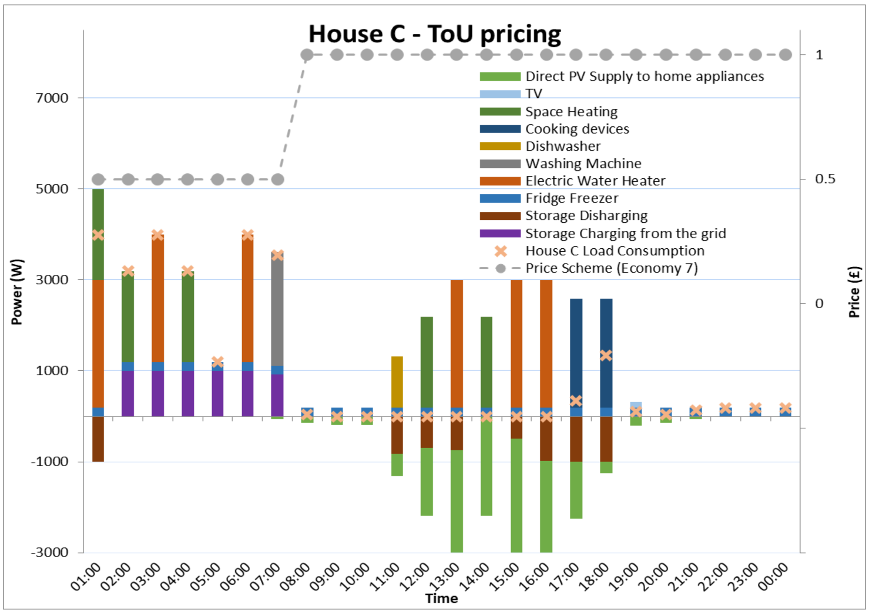


Figure 3-12 Scheduling Results of House C under ToU Tariff

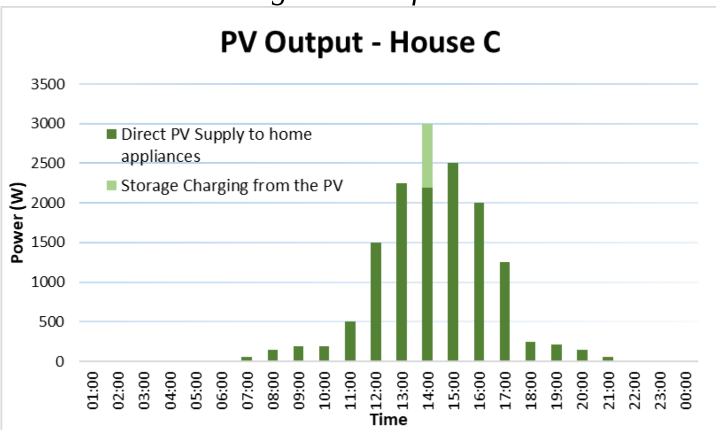


Figure 3-13 PV Output of House C

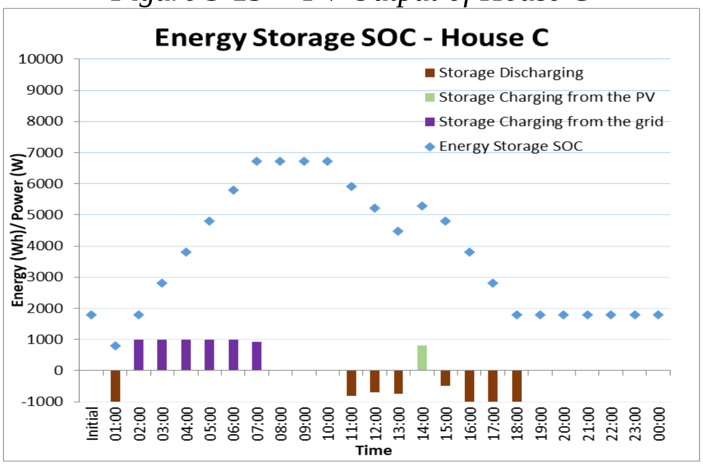


Figure 3-14 Energy Storage Charging and Discharging Activity and its SOC in House C

Detailed charging and discharging activities of the energy storage including its SOC is given in Figure 3-14. The energy storage charges from both grid supply and PV production. Since the maximum charging power of the energy storage is limited to 1kW, the energy storage is scheduled to decide if it charges from the grid or from PV production, especially when there is surplus PV production (after supplying home appliances). It can be observed from both Figure 3-13 and Figure 3-14 that the storage device charges from PV energy at 2 p.m. when the PV production reaches its maximum output. For the rest of the scheduling time, the energy storage charges from the grid supply. During the first seven hours with discounted energy price, the energy storage first discharges 1 kWh of its initially stored energy at 1 a.m. and then charges from the grid supply to take advantage of the discounted price between 2 a.m. and 7 a.m. Furthermore, the energy storage discharges between 11 a.m. to 1 p.m. and 3 p.m. to 6 p.m. The discharging activities of the battery are scheduled to minimise the energy consumption from the grid supply when the energy prices are higher.

3.2.4.5. Case Study Results of House D

House D has seven home appliances, one energy storage device and PV panels. Customers in House D consumes and sells the PV production. By generating and selling PV energy, customers in House D will receive both 'generation tariff' and 'export tariff' payments from the FIT. Moreover, the energy storage device in House C can export its stored energy to the grid to receive payments as well. It is assumed in the following case studies that the energy storage receives the same 'export tariff' as in the FIT, when it exports its stored energy.

Therefore, the scheduling tool optimises when the PV energy will be consumed directly by the home appliances, when it will be exported to the grid, and when it will be stored in the energy storage. It also decides if the stored energy in the battery will be sold to the grid. At the same time, the on/off status and working duration of the home appliances and the charging/discharging activities of the energy storage are optimised. Scheduling results of House D are given in Figure 3-15. Large consumption devices are scheduled to run when the price is low and when there are PV productions.

The detailed PV production decomposition is presented in Figure 3-16. The PV productions can be used to supply the home appliances directly, to be stored into the energy storage, and/or to be exported to the grid. Similar to House C, the majority of PV energy is supplied directly to the home appliances. The PV exports a small amount of solar energy at 9 a.m.-10 a.m. and 7 p.m., when there is surplus solar energy after satisfying the household consumption. Furthermore, the surplus PV energy is stored in the energy storage devices at 2 p.m.

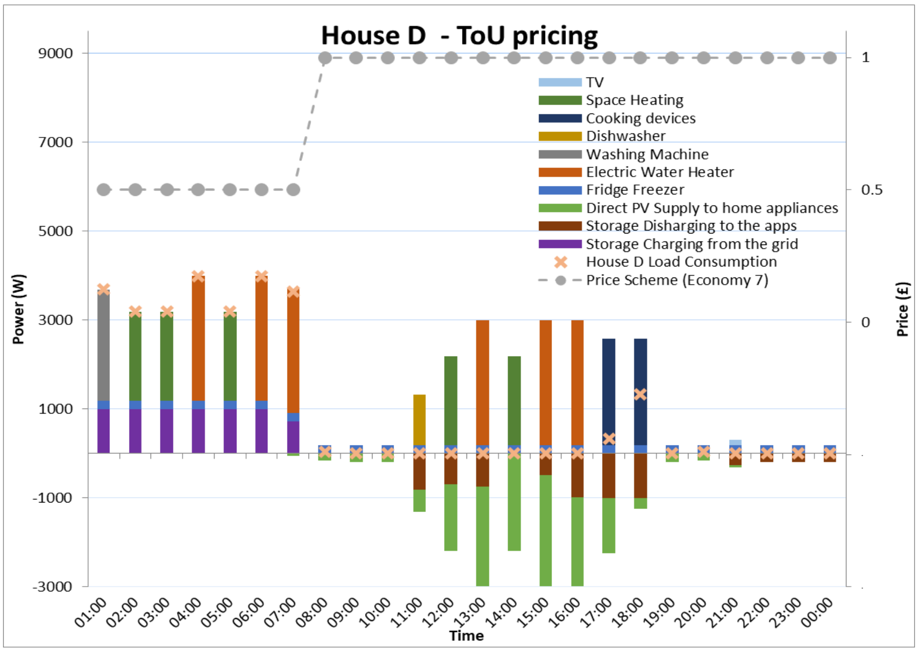


Figure 3-15 Scheduling Results of House D under ToU Tariff

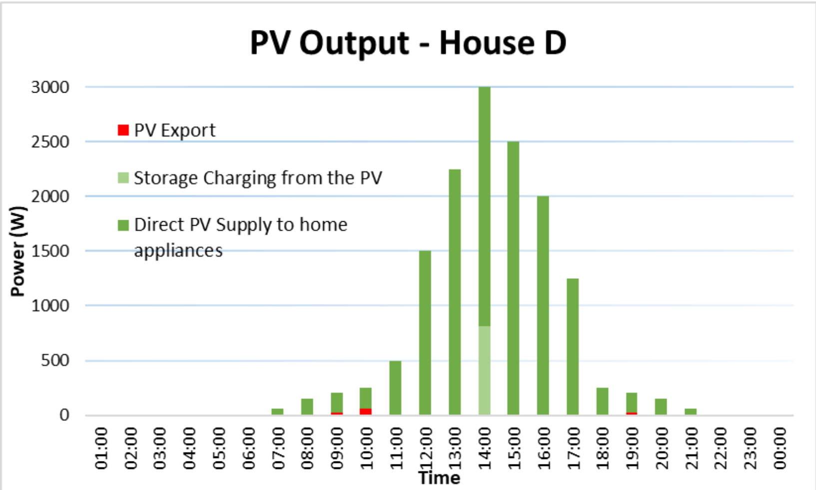


Figure 3-16 PV Output of House D

The charging and discharging activities of the storage device are illustrated in Figure 3-17, together with the SOC level of it. It can be observed the storage charges at discounted price time, from 1 a.m. to 7 a.m. It can be observed from Figure 3-16 and Figure 3-17 that the energy storage charges from the PV energy at 2 p.m. The energy storage is scheduled to discharge to lower the household consumption when the electricity price is high, at 11 a.m.–1 p.m., 3 p.m.–6 p.m., and 9 p.m.–0 a.m. As shown in Figure 3-17, the storage device discharges and exports partially stored energy to the grid from 9 p.m. – 0 a.m.

The bill payment of House D is £9.66, which is lower than that of House C (£14.11). House C and House D have the same devices, but House D can earn exportation payments by exporting the energy of the PV and the energy storage.

3.2.4.6. Case Study Results of House E

In addition to the seven home appliances, the energy storage device and the PV panels in House D, House E also has an EV that charges before and after working time. The storage device and PV panel are able to export surplus energy to the grid in House E. The same ToU pricing and FIT tariff applies to House E. With an additional EV that needs to be charged to a certain level before leaving the house, the scheduling tool also optimises when the EV charges. The capacity of the EV battery is assumed to be 40 kWh [99], and the maximum charging power of the EV is configured at 5 kW per hour. Thus, the total consumption of House D allowance is increased to 10 kW at any time during the scheduling. Scheduling results of home appliances and relevant PV and energy storage activities in House D are presented in Figure 3-18. Most of the large consumption home appliances activity is scheduled during the discounted price period, i.e. the first 7 hours.

The EV charges from 4 a.m. to 6 a.m. to reach the SOC target (35 kWh) before leaving to work at 7 a.m. The EV charging activities are also presented in Figure 3-19, as well as its SOC. It returns home at 6 p.m. with 15 kWh remaining in the EV battery. With the EV connected for charging, the scheduling tool charges the EV from 7 p.m. to 0 a.m. During this period, the EV charges from the PV supply, energy storage discharged energy and grid supply. The EV only benefits from a small amount (20Wh) energy from the direct PV supply, as the EV is not connected to the house during the majority of PV production time. During the high price period, it can be observed from Figure 3-18 that the PV and energy storage directly supply the home appliances, in order to lower the consumption. The PV production and energy storage activities are shown in Figure 3-20 and Figure 3-21, respectively.

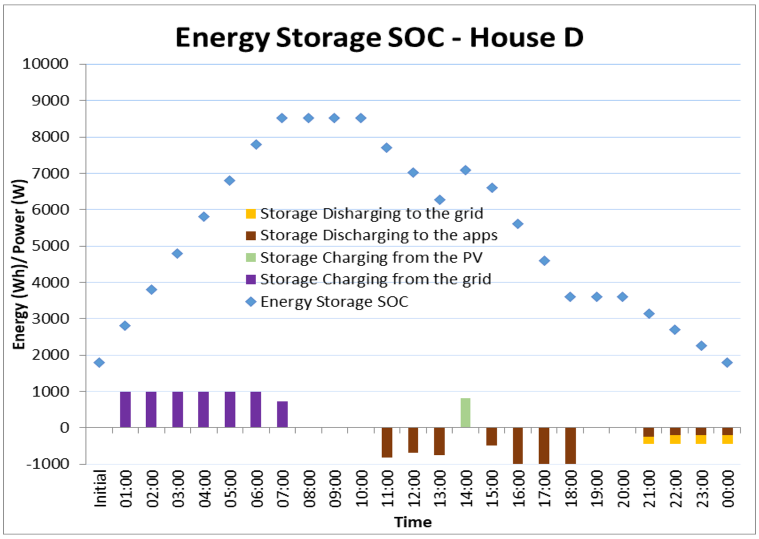


Figure 3-17 Energy Storage Charging and Discharging Activity and its SOC in House D

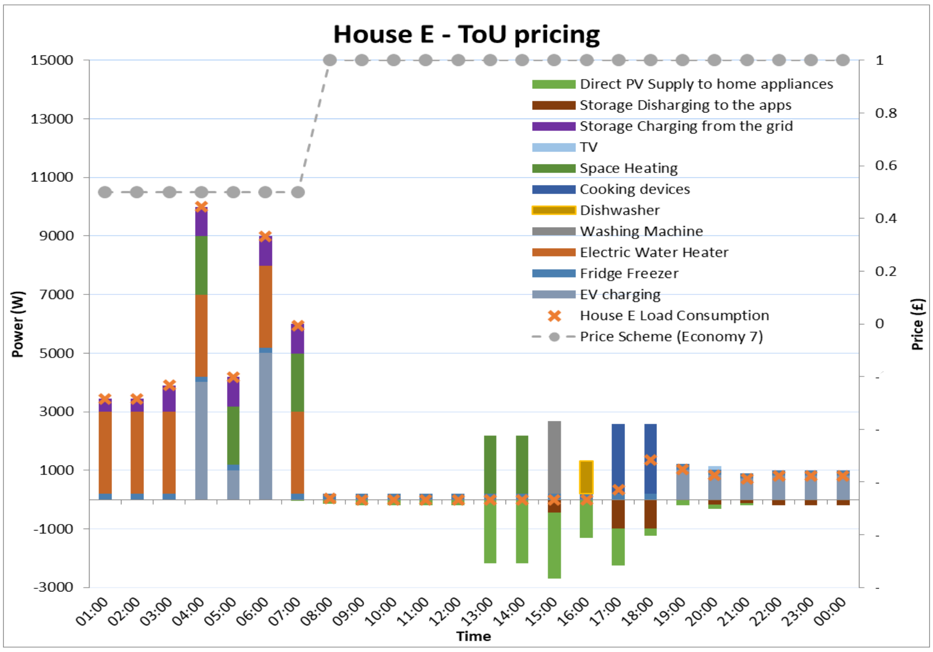


Figure 3-18 Scheduling Results of House E under ToU Tariff

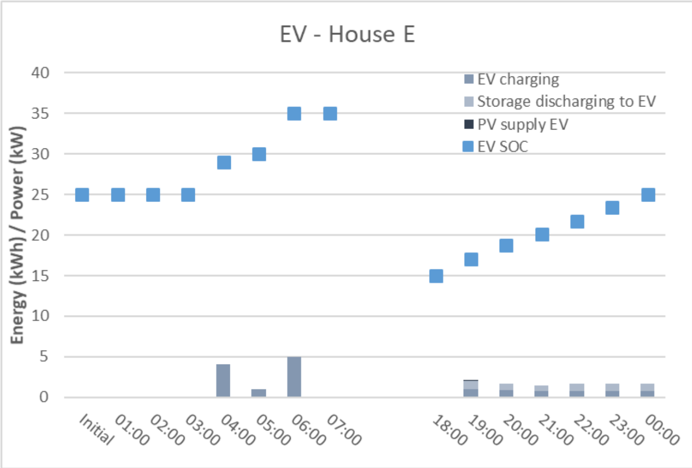


Figure 3-19 EV Activity and its SOC in House E

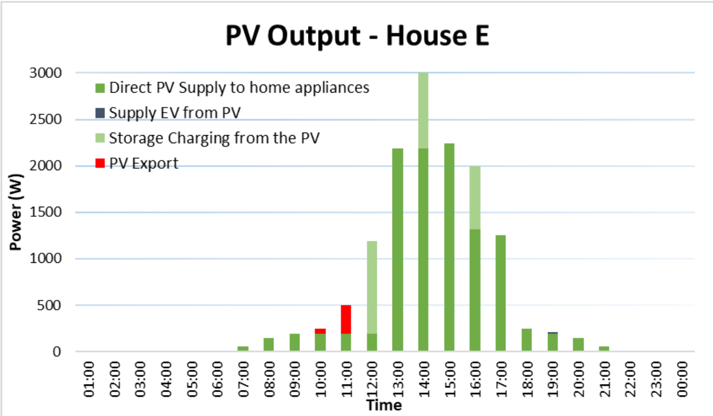


Figure 3-20 PV Output in House E

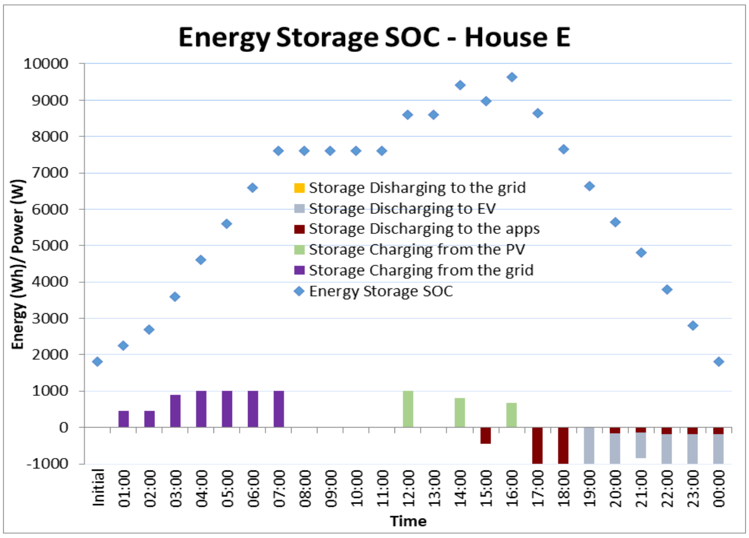


Figure 3-21 Energy Storage Charging and Discharging Activity and its SOC in House E

As illustrated in Figure 3-20, most of the PV production supplies directly to home appliances. The energy storage charges from the PV energy at 12 p.m., 2 p.m. and 4 p.m., when the PV production is over 1/3 of its capacity. At 10 a.m. and 11 a.m., the PV is scheduled to export part of its production to the grid, when the consumption of House E is low.

The energy storage device charges from the grid supply during the first 7 hours in Figure 3-21, when the price rates are discounted. Following the charge activity at the first 7 hours, the energy storage keeps charging from the PV energy between at 12 p.m., 2 p.m. and 4 p.m. The energy storage discharges from 3 p.m. to supply home appliances and charge EV. Thus, the total household consumption is lowered when the ToU price rates are high. The energy bill payment of House E is £22.37.

3.2.4.7. Case Study Results of House F

House E has six home appliances, an energy storage device, PV panels and a storage heater. The space heating in House A – E is replaced by a storage heater. The same as House C – E, the energy storage device and PV panels can export energy to the grid to earn FIT payments. The maximum consumption allowance of House E is 5 kW at any time of scheduling. The storage heater charges at maximum 1 kW per hour, and it outputs 0.5 kW equivalent heat from its stored heat energy every hour. To ensure the comfort level of the customers, a minimum level of SOC in the storage heater is used as an indicator. The SOC installed in the storage heater will not fall below the indicated minimum value (3kWh). Customers can set a target value of the heat energy (SOC) to be stored in the storage heater before arriving at home. In this case study, the SOC in the storage heater should not be lower than 7kWh (target SOC) at 6 p.m.

Scheduling results of home appliances and storage heater are presented in Figure 3-22. It shows in Figure 3-22 when the home appliances will be scheduled to run, and when the storage heater will charge from grid supply. It can be observed that at the first 7 hours of scheduling, when the energy price is low, both the energy storage and storage heater charge from the grid supply. Moreover, the water heater operates for 4 hours during the low price period. From 8 a.m., when the prices are high, to lower the energy supplied from the grid, i.e. to lower the energy bill of House F, energy storage and PV supply the home appliances and storage heater in Figure 3-22. The energy bill payment of House F is £12.63.

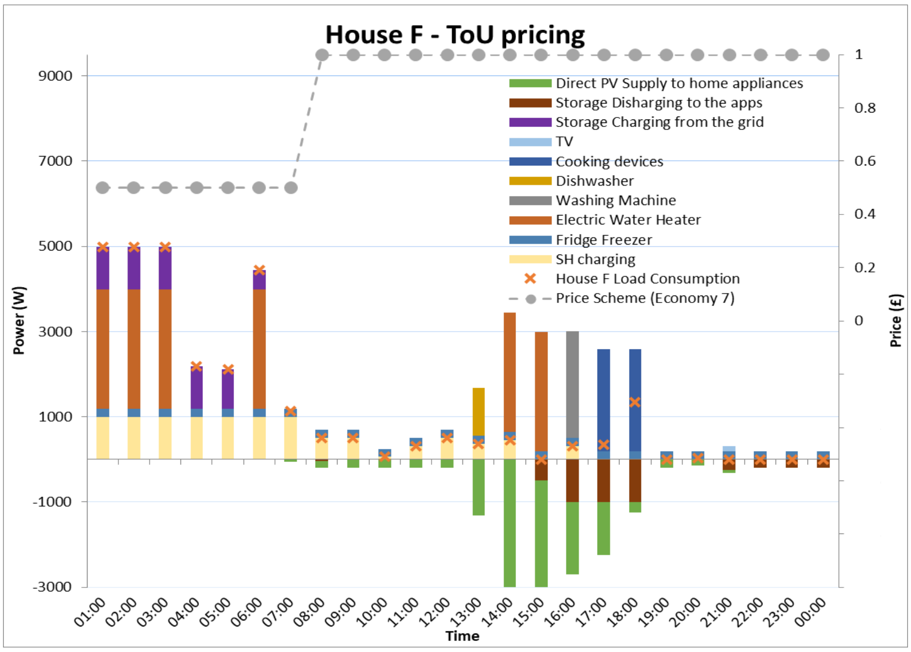


Figure 3-22 Scheduling Results of House F under ToU Tariff

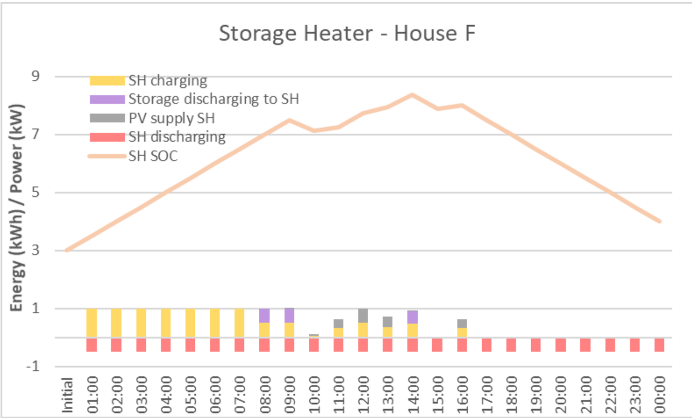


Figure 3-23 Storage Heater Activity and its SOC in House F

The activities of the storage heater and energy storage device are shown in Figure 3-23 and Figure 3-24, respectively. As Figure 3-23 indicates, the storage heater charges at full power (i.e. 1kW) from 1 a.m. to 9 a.m. At 8 a.m. and 9 a.m., the storage heater charges from the grid supply and the energy storage. With energy stored in the storage heater, it outputs 0.5kW equivalent heat every hour. Thus, the storage heater keeps charging after 9 a.m., it charges from the grid supply, the energy storage, and the PV energy. The charging activity of the storage heater stops at 5 p.m., as it can reach the target SOC at 6 p.m.

In Figure 3-24, the energy storage not only charges from the grid supply (between 1 a.m. and 6 a.m.) but also charges from the PV energy from 12 p.m. to 1 p.m. Its stored energy discharges to heat the storage heater at 8 a.m., 9 a.m. and 2 p.m., when the storage heater is charging and the energy price is high. The energy storage continues discharging to supply the appliances from 3 p.m. to 6 p.m. and 9 p.m. to 0 a.m. Moreover, part of the stored energy also exports back to the grid from 9 p.m. to 0 a.m. to earn energy exportation payment.

The PV production is shown in Figure 3-25. The majority of PV production supplies the home appliances and storage heater. As presented in Figure 3-24 as well, the energy storage charges from surplus PV energy at 12 p.m. and 1 p.m. The PV is also scheduled to export to grid 5 W at 8 a.m. and 20 W at 7 p.m.

3.2.4.8. Case Study Results of House G

House G has 6 home appliances, with the space heating replaced by a storage heater. It also has PV panels, an energy storage device and an EV connected. The same as House E, the EV has a target level of SOC (35kWh) that needs to be met before leaving the house at 7 a.m. When the EV returns home at 6 p.m., it will charge from its remaining SOC in its battery to the target level before 7 a.m. the next day. The storage heater also has a target SOC level (7kWh) at 6 p.m., so to keep the comfort level of heating in the house. The consumption allowance of House G is 10kW.

Scheduling results of the household consumption are illustrated in Figure 3-26. The water heater operates at the first 4 hours of scheduling to take advantage of low energy price. It also runs at 2 - 3 p.m. At 2 - 3 p.m., the consumption of the water heater is mostly supplied by PV energy. The cooking devices are scheduled to run at 5 - 6 p.m. when they are needed for preparing a meal. In a similar way, the PV supplies its energy to lower the consumption of cooking devices. It can be observed from Figure 3-26 that, at the first 7 hours of scheduling, the storage heater, the EV and the energy storage charge from the grid supply. Detailed activities of storage heater, EV, and energy storage are shown in Figure 3-27, Figure 3-28, and Figure 3-29, respectively.

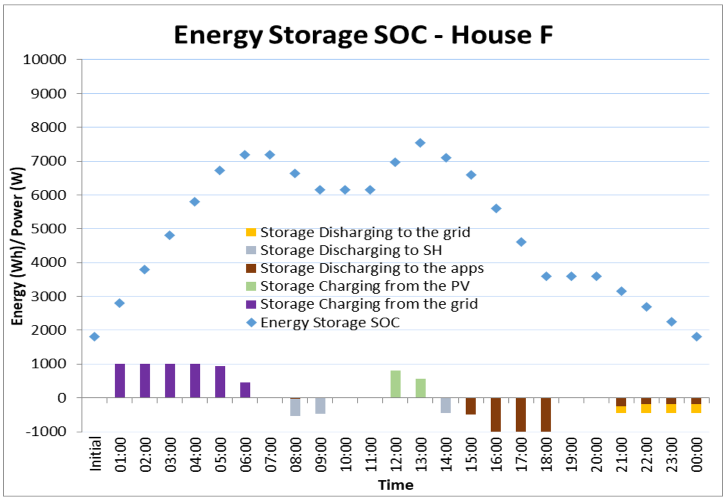


Figure 3-24 Energy Storage Charging and Discharging Activity and its SOC in House F

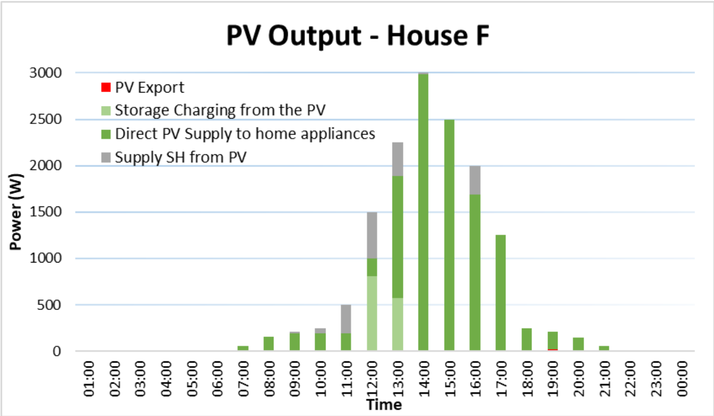


Figure 3-25 PV Output in House F

In Figure 3-27, the storage heater charges at its maximum power from 1 – 7 a.m., when the energy price is low. From 8 a.m., it charges from the grid supply, the energy storage and the PV production. Thus, by charging less from the grid supply during the high price period, the house pays less for heating.

The EV charging activities are presented in Figure 3-28. It returns to the house at 6 p.m. with 15 kWh energy left in the EV battery. From 7 p.m., the EV charges from both the grid supply and energy storage. The PV supplies a small amount to the EV at 7 p.m. (20 W) and 9 p.m. (60W), as the EV is away when the PV has energy production.

In the morning, the EV continuous its charging activity. Since 1 – 7 a.m. is the discounted price period, the EV charges from the grid supply at 1 a.m. and 3 a.m.

The energy storage also charges at the first seven hours from the grid supply to use cheaper energy supply in Figure 3-29. It then charges from the PV at 11 a.m., 12 p.m. and 4 p.m. The energy storage discharges to the storage heater, the home appliances and the EV from 1 p.m. It can be noted that the majority of energy stored in the energy storage is discharged to the EV from 7 p.m.

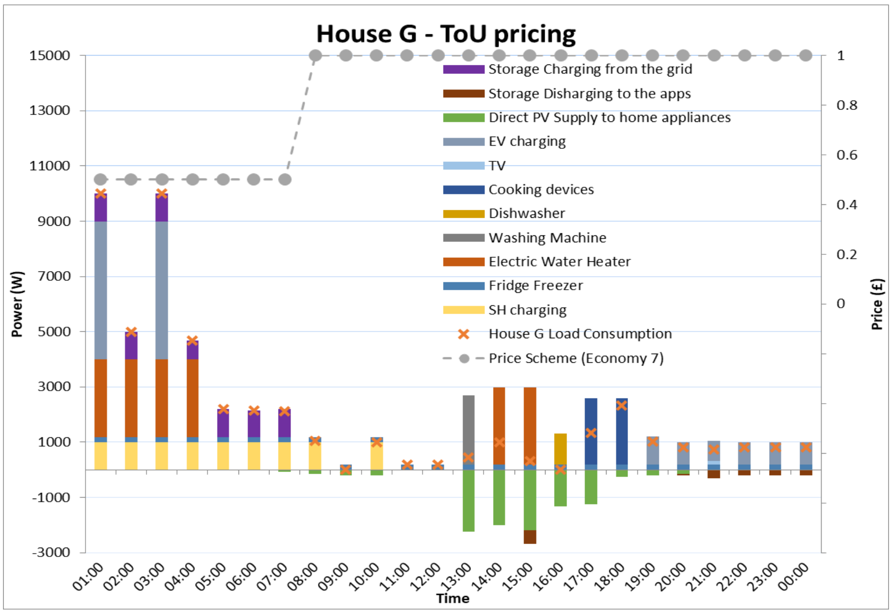


Figure 3-26 Scheduling Results of House G under ToU tariff

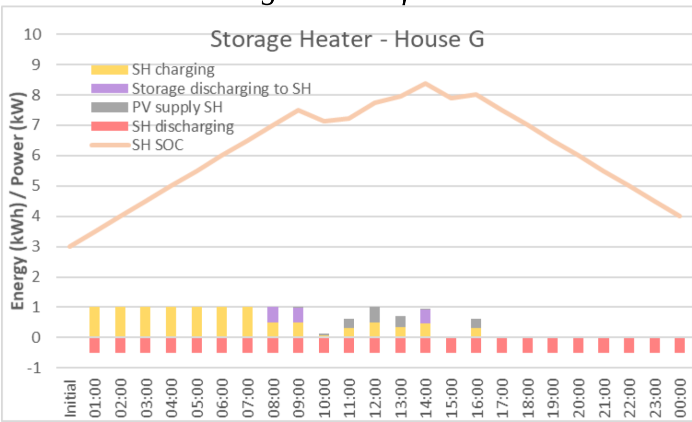


Figure 3-27 Storage Heater Activity and its SOC in House G

In addition to supplying the house consumption, the PV also exports 20 W at 9 a.m., 60 W at 10 a.m., 310 W at 12 a.m., and 10 W at 2 p.m. The PV energy production can be found in Figure 3-30.

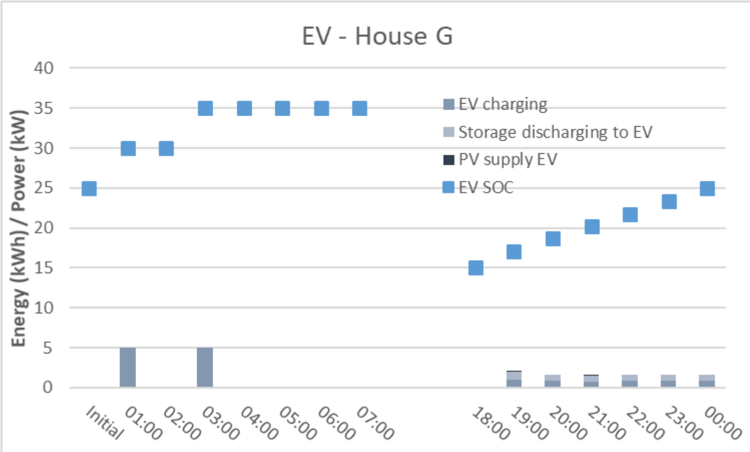


Figure 3-28 EV Activity and its SOC in House G

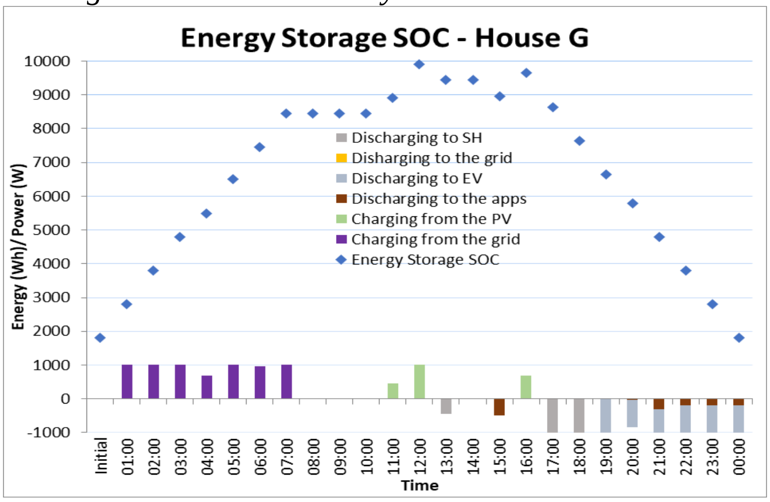


Figure 3-29 Energy Storage Charging and Discharging Activity and its SOC in House G

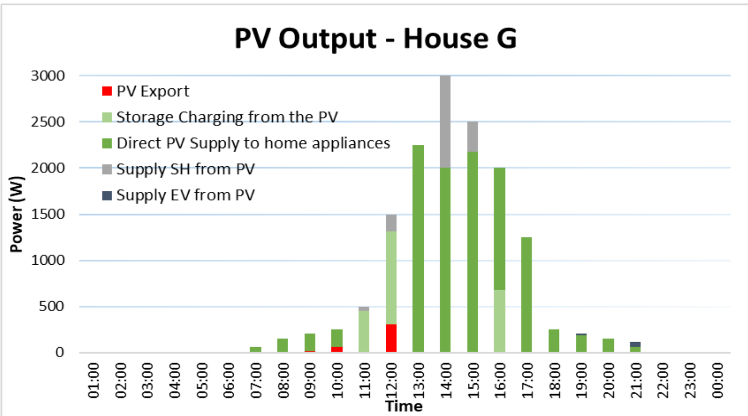


Figure 3-30 PV Output in House G

Thus, after satisfying the energy usage in the house, the PV also exports a small amount of energy to earn exportation payment. The bill payment of House G is £26.61.

3.3. Summary

Consumer-centred demand response can provide the flexibility necessary for the operation of power systems with high levels of renewable generation penetration. It is assumed demand side actively participation to drive the practical application in the individual residential household.

A scheduling tool has been developed with its aim to minimise the energy bill payment of customers, through rescheduling the devices in the individual residential households. The tool helps consumers rescheduling the devices corresponding to different pricing notifications based on their energy consumption preferences, while customers' electricity usage preferences are respected in the scheduling tool at the same time. It also gives consumers choices and options to choose if they are willing to participate and how much they are going to taking part in the scheduling, by indicating the availabilities and running time durations of the home appliances. Pre-defined (ToU) energy pricing tariff has been tested in different case studies. An energy storage device, a storage heater and an EV are also included in the test household models to explore their flexibility levels. In addition, a few test models comprise a PV system to study the optimised utilisation of PV production in the household when there are FIT payments.

The common result for all the cases is that large energy consumption devices are scheduled towards the lower electricity price time periods and/or high PV energy production time. During the higher price period, the energy storage and PV supply the house consumption. When there is no PV production in the evening, the energy storage discharges to lower the energy consumption supplied from the grid. Surplus PV energy is also stored in the energy storage. Moreover, a small amount of PV energy is exported to the grid after satisfying the energy usage in the houses.

The energy bill payments of the houses are summarised in Table 3-7. House B has an additional energy storage than House A, so the bill payment of House B is cheaper than that of House A. House C pays less than House B because it has PV panels installed. Since the energy storage and the PV panels can export their energy to the grid, House D's payment is lower than House C. House F replaces the space heating to the storage heater in House D, and the storage heater is configured to have a higher comfort level requirement, so the bill payment of House F is higher than House D. House E has an added EV comparing to House D, so House E pays more than House D. House G has the highest bill payment, because it has all the devices connected (6 home appliances, a storage heater, an energy storage device, an EV and PV panels). It is worthwhile mentioning that the electricity payment is calculated based on the illustrative Economy 7 rates employed in case studies, thus, the payment of case studies cannot be regarded as the real payment. In addition, it should be noted that the water heater and space heating are scheduled in case studies, where these two are normally supplied by gas rather than electricity in the UK. However, with the electrification of heat and transportation in the near future, the case studies can shed some lights on how the electricity payment will change.

All the case studies have sufficient evidence showing the consumer-based scheduling tool succeeded in achieving its goal, i.e. minimise the energy bill payment, by utilising the energy storage devices and the PV production. Therefore, the scheduling tool makes it possible for consumers to monitor the price signals intelligently and achieve energy bill savings automatically.

Table 3-7 Electricity Bill Payments of Each House (Case Studies)

	House A	House B	House C	House D	House E	House F	House G
Electricity Payment	£24.03	£23.03	£14.11	£9.66	£22.37	£12.63	£26.62

Chapter 4
Real Time Pricing and Demand Scheduling

4.1. Introduction

Different types of electricity price tariffs with varying rates at each hour are starting to emerge, e.g. Time of Use (ToU) pricing and Real Time Pricing (RTP). ToU pricing has been tested in the basic scheduling tool developed in Chapter 3, through using Economy 7 tariff as an example of ToU in the simulated individual residential household.

Considering the ever increasing renewable energy and DERs (Distributed Energy Resources) integration, RTP pricing where price rates calculated at frequent time intervals can reflect network conditions. RTP [58] has varying electricity price rates over time. The rates of dynamic pricing scheme are based on the outcomes of the day-ahead or real time market clearing. Thus, the stochastic real-time electricity price rates at different time slots can reflect network conditions, for example, the amount of wind generation injects into the grid at that time period.

Stochastic energy pricing has a high level of volatility, which is caused by i) balance between supply and demand and ii) generation and demand uncertainties etc. Therefore, forecasting stochastic RTP can help customers to arrange their daily energy usage patterns so to avoid unexpected expensive bills.

This chapter analyses the second type of price incentive signal – the stochastic real-time pricing, including the forecasting of RTP and demand scheduling based on the forecasted RTP. Major methods used in forecasting dynamic pricing are mentioned in section 4.2 of this chapter, and reviewed in detail in Appendix II. Forecasting method used in the research is explained in this chapter. In addition, stochastic dynamic RTP is tested in the scheduling tool.

4.2. Real-Time Pricing Forecasting

There are several approaches used for forecasting uncertain electricity prices, [102] and [103] gives a detailed review of pricing forecasting methods. Commonly used forecasting methods are reviewed in Appendix II, including artificial neural network, transfer function and Auto Regressive Moving Average (ARMA) models.

The forecasting method applied in this research for forecasting future RTP is ARMA of time series models for the next 24 hours. Comparing with deterministic electricity prices, RTPs are dynamic and they can reflect certain factors happening in the power system. ARMA model can fit in various kinds of databases for relatively good forecasting results due to its efficiency and flexibility. It is robust for short term forecast as well.

To forecast through ARMA model, there are three forms often used. They are difference equation, inverted form and random shock form. The difference equation is relevant to previous data, previous error and current error; the inverted form is in terms of previous data and current error; while the random shock form is only based on the error terms [104]. The difference equation form is used during the research progress.

Considering the forecasting value y_{t+l} at lead time l, and assuming the present value of y_t is known, use the difference equation to present the future value y_{t+l}, it is

$$y_{t+l} = \varphi_1 y_{t+l-1} + \varphi_2 y_{t+l-2} + \cdots + \varphi_{p+d} y_{t+l-p-d} - \theta_1 \varepsilon_{t+l-1} - \cdots - \theta_q \varepsilon_{t+l-q} + \varepsilon_{t+l} \qquad (4-5)$$

Equation $(4-5)$ has p autoregressive parameters $\emptyset_1$, ..., $\emptyset_p$, q moving average parameters θ_1,..., θ_q, and d differencing degrees. For the RTP forecasting, equation $(4-5)$ can be re-wrote as

$$\pi_{t+l} = \varphi_1 \pi_{t+l-1} + \varphi_2 \pi_{t+l-2} + \cdots + \varphi_{p+d} \pi_{t+l-p-d} - \theta_1 \varepsilon_{t+l-1} - \cdots - \theta_q \varepsilon_{t+l-q} + \varepsilon_{t+l} \qquad (4-6)$$

where π_t is the present value of RTP and π_{t+l} is predicted value of RTP at time $t + l$. As a result, after determining the p, d, q parameters and coefficients, the stochastic RTP and its future variables could be acquired by using the difference equation.

4.2.1. Box-Jenkins Methodology

In order to build an ARMA model, the Box-Jenkins methodology [104] is employed to determine the parameters of ARMA model. As illustrated in Figure 4-1, the Box-Jenkins method includes several general steps, which are model identification, parameter estimation, model diagnostic, and model selection. The forecasting of RTP is based on past observations of PJM [105] real-time energy prices. The past PJM energy pricing data is given in Figure 4-2. The PJM price data is used because it is publicly available and can be used to test the capability of the scheduling tool.

The first step of the Box-Jenkins method is *model identification*, with the aim to identify the type of ARMA model and its p, d, and q parameters. If possible seasonal or periodic characteristic is detected with the stochastic process, SARIMA may be suitable for the models. However, it can be observed from Figure 4-2 that there is no strong seasonality feature exists in the PJM pricing data. Therefore, ARMA is applied to forecast the dynamic pricing.

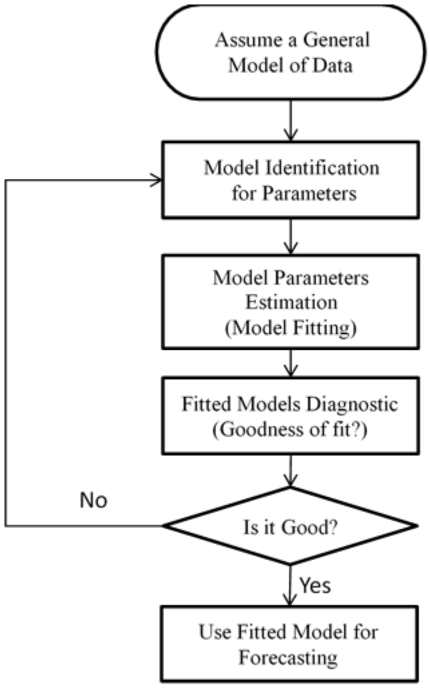


Figure 4-1 Flow Chart of Box-Jenkins Methodology

After determining the type of model, the stationary of the stochastic process should be assessed, considering ARMA models fit stable datasets which have a stationary and constant mean value. There are several spikes with dramatically high values can be noticed in Figure 4-2. As aforementioned, a more stable model could be achieved by applying logarithm to nonstationary processes. As a result, a logarithm with 10 as the base is applied to process the original electricity dataset. Figure 4-3 gives a comparison between the original PJM data and logged pricing data, in which a stable logged pricing dataset can be found after the log transformation. Therefore, the ARMA forecasting starts on the basis of transformed logged price data. Furthermore, since a stationary data is achieved through a logarithm operator, the d differencing degree will not be considered (i.e. d = 0) during the rest of the model identification procedure.

At the model identification step, the remaining two (p and q) parameters of the ARMA model are determined, which define the value of the corresponding AR operator and MA operator. The p and q parameters are identified through the trend of both Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF). The ACF reveals the correlation relationship between any two values of the series data. Another way to measure the connections between any two values of the series is to filter out the linear dependence of variable lie in between these two values in the series, and calculate the correlation relationship of the transformed series data, which is PACF. The behaviours of both ACF and PACF indicate the possible values for p and q. A detailed description of the association between trends of both ACF, PACF and the identification of model parameters can be found in [104], where Table 4-1 gives a brief summary. An initial configuration of both ACF and PACF are equal to 1 at lag 0. If the ACF curve of the model decays relatively slow and it does not 'die out' for moderate and large lags, it implies the underlying stochastic process is nonstationary.

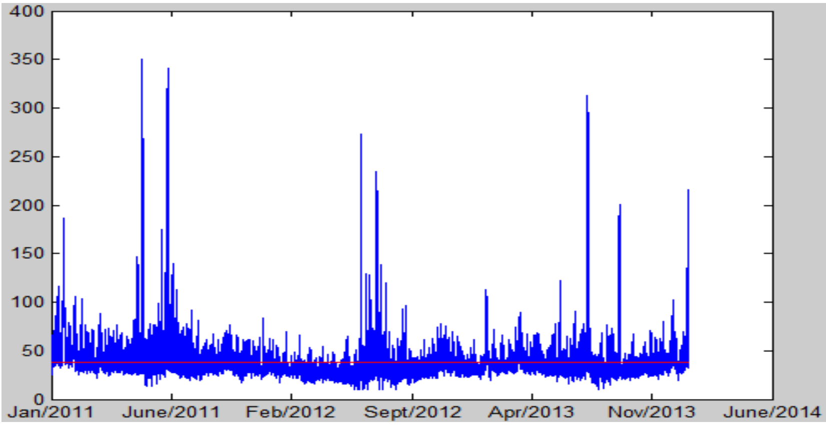


Figure 4-2 Historical PJM Energy Pricing ($/MWh)

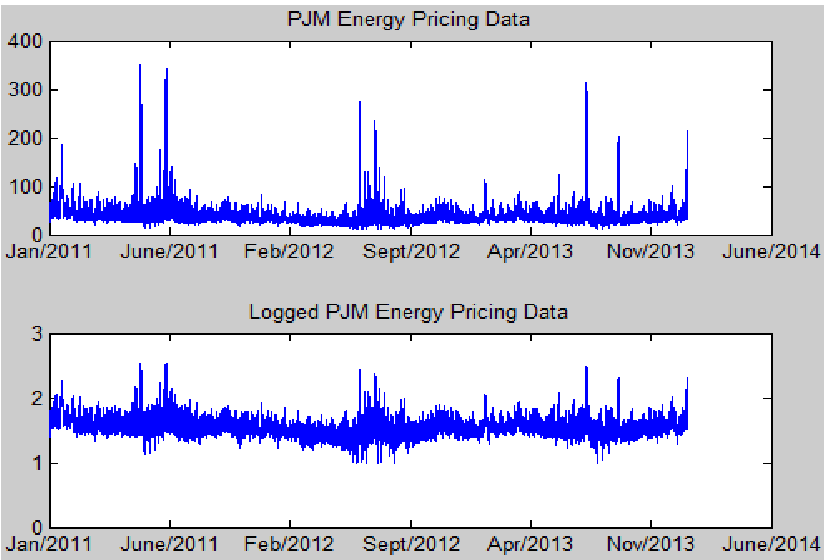


Figure 4-3 Historical PJM Energy Pricing ($/MWh) and Its Log-processed Pricing Data

Table 4-1 Summary of ACF and PACF Behaviours

	ACF	PACF
AR(p)	Tails off	Cuts off after Lag p
MA(q)	Cuts off after Lag q	Tails off
ARMA(p,q)	Tails off	Tails off
	a mixture of exponential and damped sine waves after the first q − p lags	

The ACF and PACF of the logged PJM energy pricing data are calculated and presented in Figure 4-4. First of all, the logged PJM data is stationary as it can be observed that the ACF trend as the ACF 'dies out' quickly. There is an obvious value change in PACF at lag 2, therefore, two possible types of ARMA model could fit, which are AR models and ARMA models. If the value change of PACF at lag 2 is considered as cut off, an AR (2) model is a possible fit for the pricing data. Furthermore, the correlations decrease fairly regularly in ACF, and a mixture of periodic damping sine wave and decaying exponential curve can be detected from the ACF trend. This indicates a possibility that the logged PJM data is a mixed ARMA problem. Therefore, ARMA (2, 2), ARMA (3, 3), and ARMA (4, 4) could possibly be used for time series analysis for the original model. The trend of PACF tends to support this possibility.

To summarise, at the *model identification* step, AR (2), ARMA (2, 2), ARMA (3, 3), and ARMA (4, 4) are the possible models.

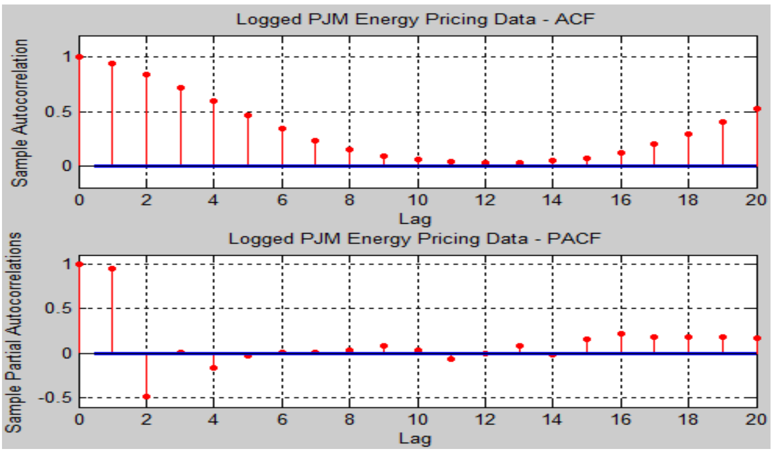


Figure 4-4 ACF and PACF of Logged PJM Energy Pricing Data

After identifying potential models at the *model identification* step, the values of AR and MA parameters of each possible time series model need to be estimated at the *model parameters estimation* step. Maximum Likelihood Estimation (MLE) method is applied during the estimation procedure based on the logged PJM energy pricing data. MLE is the most general and popular parameter estimation method, and [104], [106, 107] explains the details of MLE technique.

The likelihood function is defined as $L(\xi|y)$, where y is a sample of data with a known probability distribution and ξ is a set of parameters. The $L(\xi|y)$ denotes the likelihood of the parameter ξ when data y is given, which is a function of ξ. An example of the likelihood function is presented in Figure 4-5 [107]. One of the advantages of the likelihood function is it is able to include all the information contained in the data y. The method of finding values of the parameters that maximise the likelihood function is the MLE. Therefore, MLE is one solution to the likelihood function. The MLE can cope with a wide range of data processes, but it always involves large computational efforts. For computational convenience, the log-likelihood calculation is often used.

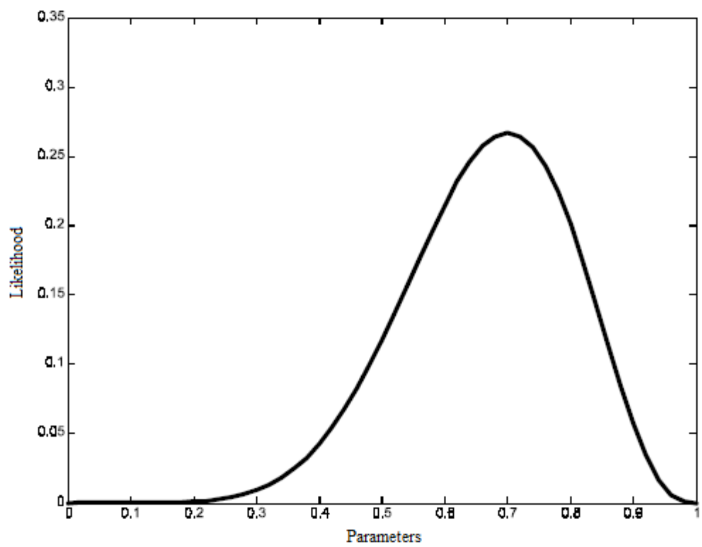


Figure 4-5 One Example of Likelihood Function [107]

The *model parameters estimation* process is computed with the aid of MATLAB software [108] due to calculation complexity, by means of MLE method. Parameters of the AR and MA in ARMA time series models are determined with the aim to find the closest match to the logged PJM energy pricing data. When applying the MLE, the optimized log-likelihood objective values of each model are generated during the estimation stage. The optimised log-likelihood objective values will be used for model diagnostic and comparison at the following steps.

As a result, at the *model parameters estimate* step, parameters of identified models are determined through the MLE method, by fitting the time series models to the historical pricing dataset. The values of the p autoregressive parameters $\emptyset_1$,..., $\emptyset_p$ and q moving average parameters θ_1,..., θ_q are obtained at this step.

The potential time series models and their parameters have been defined and determined at *model identification* and *model parameters estimation* steps. At the *model diagnostic* step, it evaluates and examines the possible fitted models. Box-Jenkins method proposes to check residuals from the fitted models to decide if the fitted models are adequate [104, 109]. The residual is defined as the difference between the stochastic process and the fitted model. The purpose of using residuals for diagnostic the possible models is to observe if the residuals are reasonably uncorrelated and approximately normally distributed. If the residuals meet both of the criteria, it can be concluded that the ARMA model is appropriate for modelling the stochastic process.

Residuals are calculated and plotted for each identified potential time series model, which are AR (2), ARMA (2, 2), ARMA (3, 3), and ARMA (4, 4). Results of residuals of AR (2) and ARMA (4, 4) model are presented in Figure 4-6 and Figure 4-7, respectively. Distribution of residuals is shown in the top two plots, which is illustrated through a normal plot and a histogram plot. From both residual results of AR (2) and ARMA (4, 4) model, the residuals have zero mean values and constant variances. Furthermore, the histograms indicate the residuals are approximately normally distributed. The bottom two plots in Figure 4-6 and Figure 4-7 are the resulting residual ACF and PACF. Based on the ACF and PACF results of both time series models, it can be observed that the values of ACF and PACF are small, which means there is no unexplained correlation of the residuals. Therefore, all the possible ARMA models passed the *model diagnostic* procedure since the residuals of these models are approximately normally distributed and uncorrelated. These models could be used for RTP forecasting.

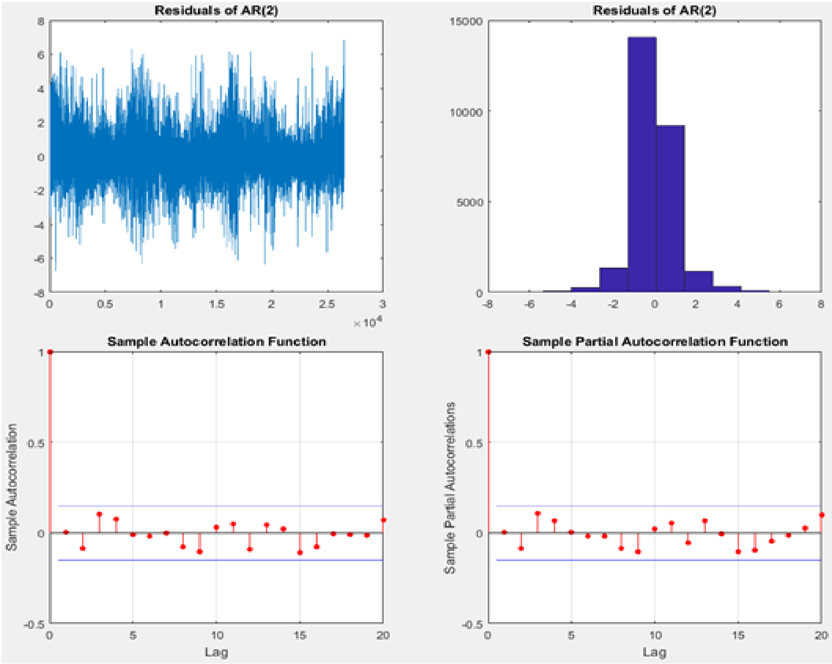


Figure 4-6 Residual Distribution, Residual ACF and PACF of AR (2) Model

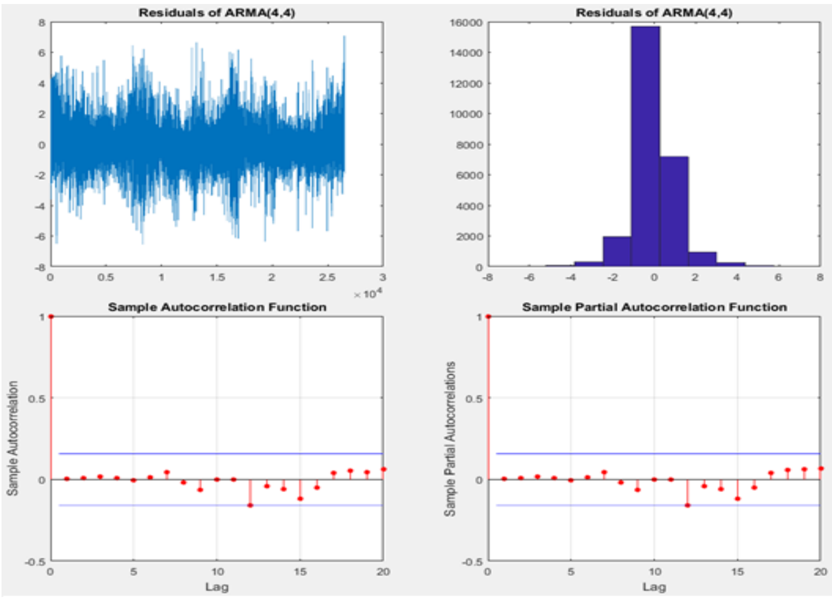


Figure 4-7 Residual Distribution, Residual ACF and PACF of ARMA (4, 4)

Although there are four possible time series models are proposed and fitted to the logged PJM energy pricing data, only one of the four models is going to be applied for analysis and forecasting future RTP data. As a result, one additional step of *model selection* is needed to filter out a better time series model. An approach to *model selection* is to use information criteria such as Akaike Information Criterion (AIC) [110] and Bayesian Information Criterion (BIC) [111]. The advantage of information criteria selection is it can be employed to compare various models fit the same data. AIC and BIC calculations are based on the optimised log-likelihood values obtained through the MLE during the *model parameters estimation* step and the number of parameters estimated for each fitted model. In addition, since the number of parameters is considered in the AIC and BIC calculations, they are able to indicate excess inclusion of parameters in fitted models.

The AIC and BIC criteria are employed at *model selection* step, models with smaller calculation results are preferred. The calculated AIC and BIC values of each possible fitted model are given in Table 4-2, which are calculated based on the optimized log-likelihood objective value. Since smaller values of AIC and BIC imply better-fitted model, ARMA (4, 4) is selected out of the four possible time series models. As a result, forecasting of RTP will be based on the ARMA (4, 4) time series model. The parameters estimated for ARMA (4, 4) model are presented in Table 4-3, including four AR, four MA parameters, and variance of the error term. The error term follows a random Gaussian distribution with constant zero mean and standard variance equals to one. Please note the reason the variance is 0.016 of the ARMA (4, 4) model is that the model fitting is performed with the past PJM energy price data after applying the logarithm transformation.

In addition to using AIC and BIC information criterion, to indicate the goodness of fit, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are also calculated. The RMSE and MAE measure the difference between simulated data and real observed data, which are commonly used in numerical model validation. The definitions of both RMSE and MAE can be found in [112]. Both measurements of errors indicate how close the ARMA models to the real observations of prices. Generally, the smaller the value of the errors implies a better fit and prediction of the original stochastic process. The resulting RMSE value of the selected ARMA (4, 4) model is 0.2 and MAE of that is 0.15, which is calculated based on forecasted data generated by ARMA fitted models and real PJM dynamic energy pricing data. The RMSE and MAE values indicate the ARMA model is well fitted for the PJM data.

Table 4-2 AIC and BIC Results of the Potential ARMA Time Series Models

	AR (2)	**ARMA (2, 2)**	**ARMA (3, 3)**	**ARMA (4, 4)**
AIC(1.0e+04 *)	-9.43	-9.48	-9.51	-9.65
BIC(1.0e+04 *)	-9.43	-9.48	-9.51	-9.64

Table 4-3 Values of Parameters for the ARMA (4, 4) Model

AR parameter $\emptyset_1$	AR parameter $\emptyset_2$	AR parameter $\emptyset_3$	AR parameter $\emptyset_4$
2	-1.099	-0.339	0.378
MA parameter θ_1	MA parameter θ_2	MA parameter θ_3	MA parameter θ_4
-0.647	-0.304	0.513	0.233
The variance of random Gaussian distributed error term ε_t		0.0016	

4.3. Real Time Pricing and Demand Scheduling

The selected ARMA (4, 4) time series model is applied for forecasting next 24-hours RTP based on the past PJM real-time energy pricing data. In order to acquire potential scenarios of future RTP, necessary scenario generation and reduction techniques are applied. There are various approaches for generating forecasting scenarios and selecting scenarios from the generated set, and the approaches will be overviewed in Chapter 5, as well as the techniques used for generating and selecting RTP scenarios in the research. Forecasting scenarios of electricity prices in the next 24 hours are generated on the basis of ARMA (4, 4) model's error term ε_t, through randomly sampling the distribution of ε_t. As mentioned above, the error term ε_t follows a Gaussian distribution with zero mean value and constant deviation. The research uses the PJM publicly available RTP data to study how the residential loads will react to the future RTP tariff, considering electrification of heat and transport.

The dynamic pricing scenarios are tested into House B, House D and House G for observing virtual consumers' responses and testing the capability of the scheduling tool. The devices included in these three houses are listed in Table 4-4. House B has seven home appliances and one energy storage device. House D has seven home appliances, one energy storage and PV panels. Moreover, the energy storage device and PV are able to export energy back to the grid to earn payments. The 'export' tariff is configured as 90% of the RTP rates. One of the seven home appliances is the space heating, House G replaces the space heating to a storage heater. Thus, House G has six home appliances, one storage heater (replaces the space heating), one energy storage, one EV and PV panels. Both the storage heater and EV has a target level of the energy stored at a target time, in order to ensure customers' comfort level and needs. The scheduling aim is to minimise the energy bill costs of customers. Detailed equations, including objective and constraints, can be found in section 3.2.3.2, section 3.2.3.4 and section 3.2.3.7 of Chapter 3, respectively. The price term of the grid supply in the objective functions are altered to the forecasted RTP scenarios.

One representative forecasted RTP scenario is selected from the generated scenario set, which is presented as the upper curves in Figure 4-8. The starting point of the RTP scenario is high due to the last value of the historical PJM energy pricing data is high. The last month of the past PJM data is January, and energy prices in January are likely to be more volatile due to unusual consumer usage patterns. However, it can be observed that the overall pricing during the forecasting 24-hours period is on an average level at around 45$/MWh, which is similar to the average value of the past prices in Figure 4-2. The price scenario has higher prices from 7 a.m. to 1 p.m. and after 9 p.m. Scheduling results of the RTP scenario in House B, D and G, using the basic scheduling tool are shown in the following sections.

Table 4-4 Summary of Devices in House B, D & G

Virtual Households	Household devices
House B	seven home appliances + one energy storage device
House D	seven home appliances + one energy storage device + PV (Energy storage and PV are able to export energy)
House G	six home appliances + one energy storage device + one EV + one storage heater + PV panels (Energy storage and PV are able to export energy)

4.3.1. Case Study Results of House B

The scheduling results of House B corresponding to the RTP scenario are shown as the bottom curves in Figure 4-8. Home appliances in House B are scheduled when the energy prices are lower. The energy storage discharge at 4 p.m. to keep the power consumption in House B remain within the consumption allowance of 5kW. Detailed charging and discharging activities of the energy storage is given in Figure 4-9. The cooking devices can only run at after work hours, therefore, they are scheduled to operate at 6 – 7 p.m. The energy storage discharges at 7 p.m. to lower the consumption of the cooking devices, so to lower the overall bill payment. The SOC of the energy storage at the end of the schedule stays the same as that at the start.

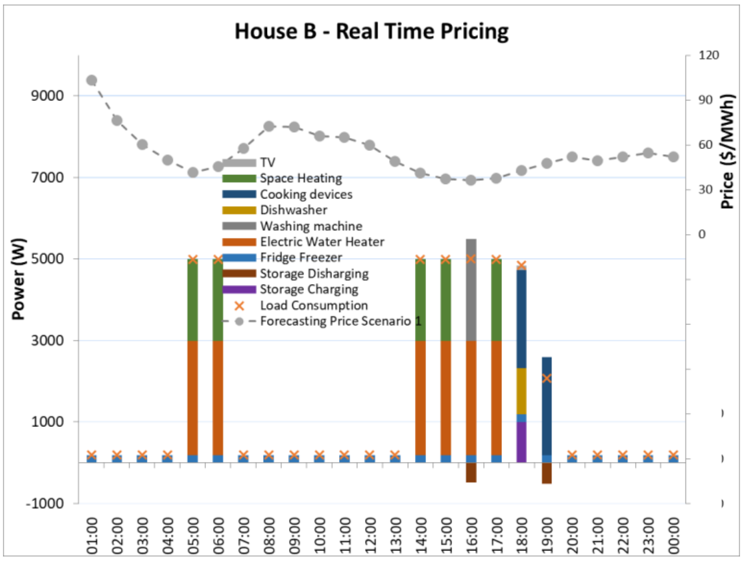


Figure 4-8 Scheduling Results of House B under Forecasted RTP

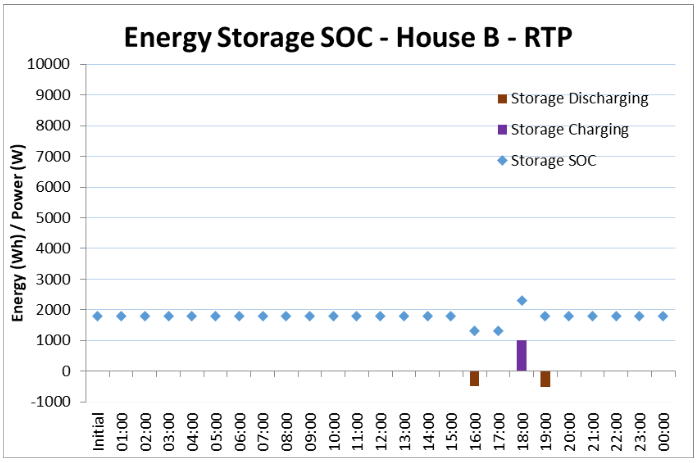


Figure 4-9 Energy Storage Charging and Discharging Activity and its SOC in House B under Forecasted RTP

4.3.2. Case Study Results of House D

Scheduling results of House D under the RTP scenario can be found in Figure 4-10. The scheduling takes advantage of lower energy prices. It schedules the home appliances to run during the lower energy price periods. The activities of the energy storage are presented in Figure 4-11. It first discharges its initial stored energy to supply home appliances at 1 – 2 a.m. During this period, it also exports energy to the grid after satisfying the home appliances consumption. This is because the energy price is high between 1 – 2 a.m., thus the 'exportation' price is high as well. The energy storage then charges from 4 to 7 a.m. and exports its stored energy between 8 and 11 a.m. From 2 p.m. to 7 p.m. the energy storage charges from the grid supply and the PV production. At the last three hours of the scheduling, it exports part of its stored energy after meeting the household consumption. Therefore, the energy storage charges at lower price periods and from the PV, then discharges to the grid during high price time to earn exportation payments.

PV production under the real-time pricing scenario is shown in Figure 4-12. It can be observed that most of the PV production supplies the home appliances consumption, especially between 1 and 5 p.m. By supplying the home appliances from the PV, the house consumption is kept within the 5kW limit. From 9 a.m. to 1 p.m., the PV exports its surplus energy to the grid rather than storing the energy, as the 'exportation' prices (equals to 90% of the RTP price) are high during this period.

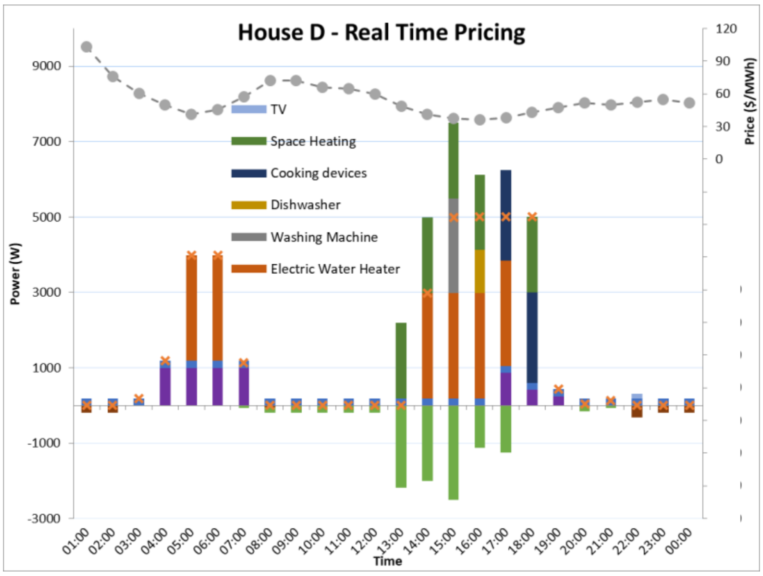


Figure 4-10 Scheduling Results of House D under Forecasted RTP

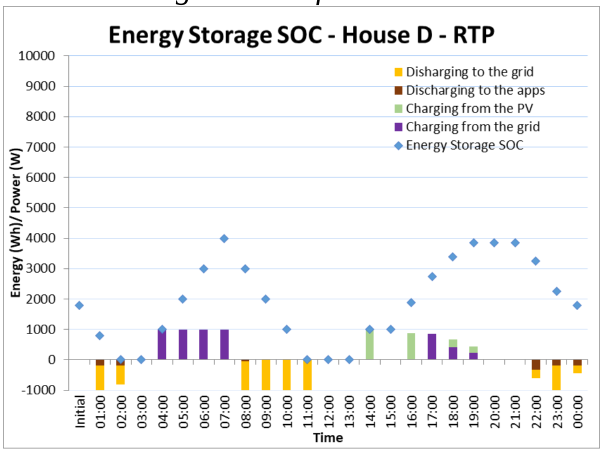


Figure 4-11 Energy Storage Charging and Discharging Activity and its SOC in House D under Forecasted RTP

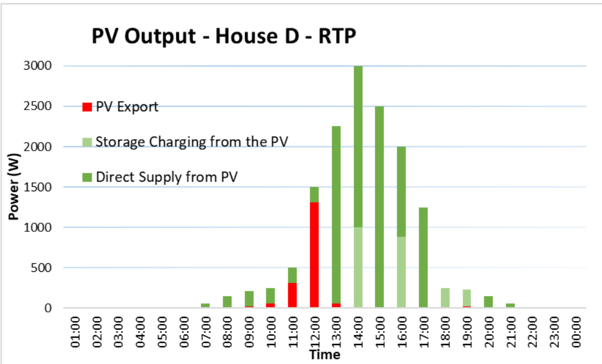


Figure 4-12 PV Output of House D under Forecasted RTP

4.3.3. Case Study Results of House G

Scheduling results of House G under the RTP scenario is illustrated in Figure 4-13. The energy consumption allowance of House G is increased to 10kW, considering the added EV and storage heater. The home appliances are scheduled at time periods when prices are low. Furthermore, the PV supplies part of the home appliances consumption between 2 and 5 p.m., as shown in Figure 4-14. The energy storage charges from the PV production from 1 to 4 p.m., when the PV production is high, which is also presented in Figure 4-15. In addition, the PV supplies the storage heater at 2 p.m. From 9 a.m. to 1 p.m., the PV exports the majority of its energy to the grid, as the exportation prices are high during the time. The energy storage also exports to the grid at 1 – 2 a.m., 8 – 11 a.m. and 11 p.m., when the prices are high. It discharges to supply the EV charging from 7 p.m. when the EV returns to the house. The charging activity of the EV is detailed in Figure 4-16. The EV also charges a small amount of energy from the PV production at 7 and 9 p.m. The remaining energy that charges the EV battery comes from the grid supply.

The storage heater is supplied by energy storage between 1 and 2 a.m. It then charges from the grid supply between 3 – 7 a.m., as given in Figure 4-17. Its charging

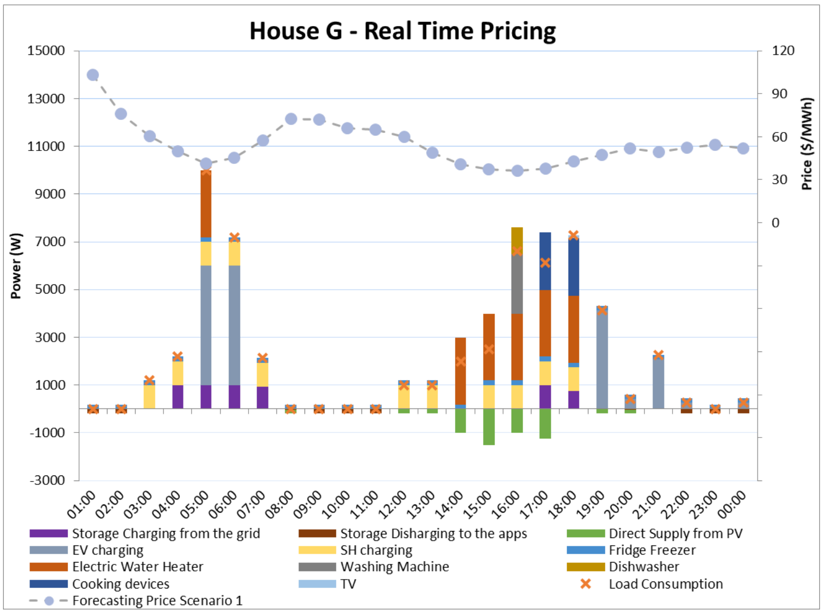


Figure 4-13 Scheduling Results of House G under Forecasted RTP

activity stopped between 8 and 11 a.m. when the prices are high. Starting from 12 p.m., it continues the charging activity. At 2 p.m., it charges from the PV production. At 6 p.m., it reaches its target SOC level of 7kWh.

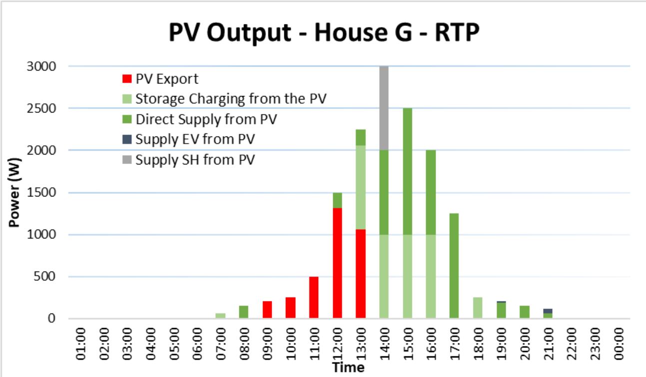


Figure 4-14 PV Output of House G under Forecasted RTP

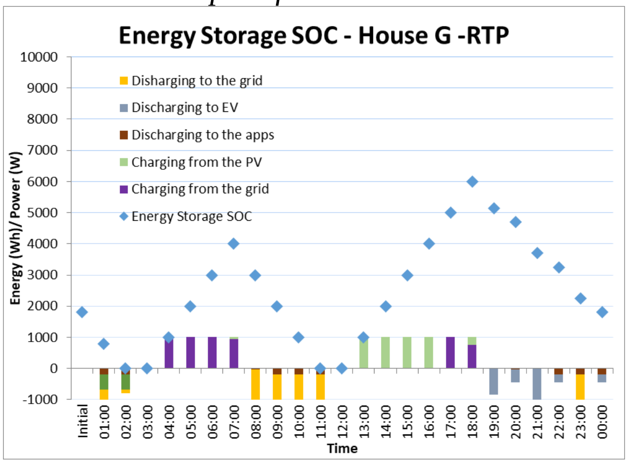


Figure 4-15 Energy Storage Charging and Discharging Activity and its SOC in House G under Forecasted RTP

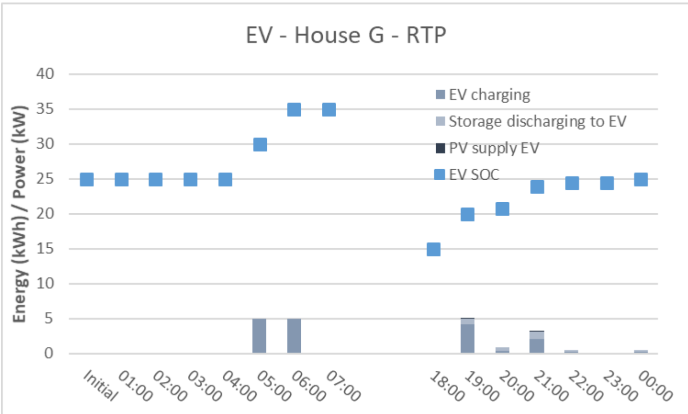


Figure 4-16 EV Activity and its SOC in House G under Forecasted RTP

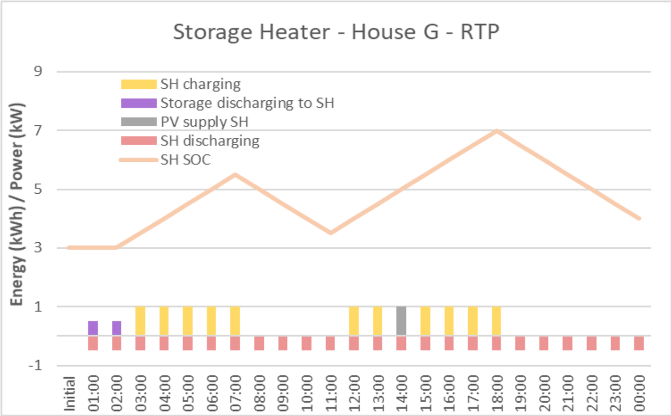


Figure 4-17 Storage Heater Activity and its SOC in House G under Forecasted RTP

4.4. Summary

In addition to ToU pricing tariff, dynamic real-time pricing starts to be available to consumers as an alternative pricing approach nowadays. The stochastic RTP reflects certain network condition, such as network imbalance and congestions etc. Therefore, RTP is analysed and applied as the second type of pricing tariff into the developed basic scheduling tool.

This chapter has reviewed two categories of major forecasting methods used for predicting future energy prices, which are artificial intelligence method and time series models. Among the methods reviewed, ARMA time series model is selected and applied in this research to forecast future RTP prices. This is because ARMA models are robust, which means the price prediction won't be affected adversely by other elements, such as weather conditions, etc.

The Box-Jenkins methodology is employed to build up an ARMA model, and the past RTP data is based on PJM real-time energy pricing data. The steps to build up an ARMA model is summarised as

i) *Model identification:* this step determines the parameters of potential ARMA model.

   a. Check if the stochastic process, i.e. past PJM price data, is stationary, with constant mean and variance. If the data is unstable, it needs to be processed. A logarithm transformation is applied to original past PJM energy price data, due to the price data is not stationary.

b. Plot the ACF and PACF of the processed (i.e. logged) stationary price data to define parameters of potential ARMA models. Based on the behaviour of ACF and PACF, AR (2), ARMA (2, 2), ARMA (3, 3) ARMA (4, 4) are determined as possible models to be fitted.

ii) *Model parameters estimation*: this step fits the possible ARMA models and estimates the pre-determined model parameters' values by means of maximum likelihood estimation method.

iii) *Model diagnostic:* this step evaluates and examines the possible fitted ARMA models through checking residual of each model is reasonably uncorrelated and approximately normally distributed. If the residuals meet both of the criteria, it can be concluded that the ARMA model is appropriate for modelling the stochastic process.

iv) Due to a number of possible ARMA models are fitted, an additional step to select a better model is essential. AIC and BIC information criteria are calculated, and ARMA (4, 4) model is selected because it gives better AIC and BIC results. RMSE and MAE of the ARMA (4, 4) model are also considered. The resulting RMSE value of the selected ARMA (4, 4) model is 0.2 and MAE of that is 0.15, which indicate the ARMA model is well fitted for the PJM real-time energy pricing data.

In the last section of this chapter, one forecasted scenario of future RTP is tested as input pricing signals in the basic scheduling tool proposed in Chapter 2. The forecasted RTP scenarios are selected through scenarios generated by ARMA (4, 4) time series model. Scenario generation and reduction techniques will be covered in the next chapter. House B, House D and House G are used to test the scheduling tool, to study its scheduling capability when facing changing RTP rates. The scheduling results show that the basic tool succeeded in minimising customer's energy bill costs, by reacting to the dynamic RTP rates.

Chapter 5
Multi-Stage Real-Time Pricing Scenario Tree

5.1. Introduction

Real-Time Pricing (RTP), with dynamic rates, is subject to uncertainty coming from the energy network situations due to the correlation between RTP and market clearing prices. As mentioned before, the hour-to-hour change of RTP rates reflects network conditions, such as network imbalances and congestions, network available generation capacity (including the renewable available generation), amount of energy consumption, and so on. The inherent uncertainty of RTP has been modelled and forecasted through an ARMA (4, 4) time series model in Chapter 4, based on past PJM real-time energy pricing data.

Forecasted RTP, as an alternative pricing approach to Time of Use (ToU) pricing, has been used as input data into the basic customer-centred scheduling tool in order to test the ability of the optimisation tool when it is facing frequent-changing energy pricing signals. By including stochastic input data, optimization problems with uncertainty are typically difficult to solve due to lack of knowledge on the true distribution of the random process. One approach is to find approximate stochastic process before solving the stochastic programming problems [113, 114].

Considering the high volatile characteristic of RTP, multi-stage scenario tree containing a finite set of possible future RTP prices with corresponding probabilities of occurrence is one of the common ways to characterise the continuous random rates of RTP. The number of stages is defined over the optimization horizon, and each stage refers to a time point when decisions are made. The information regarding the stochastic RTP is revealed gradually with the process of moving to the next stage. A two-stage scenario tree is decided to be established for predicting future RTP in this research. Detailed descriptions of the scenario tree can be found in section 5.2 of this chapter.

The stochastic values of RTP evolve sequentially over time, and the dynamic RTP depend on the past price data. In this research, a number of RTP scenarios are generated by sampling distribution of the error term in the ARMA (4, 4) model. After generating a set of scenarios, a necessary procedure of scenario reduction is applied to reduce the size and to select representative scenarios, since a large number of scenarios generated will increase the computation burden of the stochastic programming. Although the size of the scenarios is reduced, the information contained in the reduced set should be close to the original stochastic process. Two categories of scenario reduction techniques are used for scenario reduction, which are heuristic algorithm based on probability distances [115-117] and clustering [118-120]. In addition, the scenario trees which include the reduced scenario subsets resulting from the scenario reduction methods, are evaluated with the aid of basic scheduling tool. Therefore, scenario generation, scenario reduction, and methods used to assess qualities of scenario trees will be reviewed in this chapter, including the approaches employed in the research.

The established two-stage scenario tree will be combined with a rolling planning technique to enhance the basic consumer-centred scheduling tool, so to react to stochasticity coming from the energy network, which forms a stochastic consumer-centred scheduling tool. The rolling planning technique and the stochastic tool will be introduced in Chapter 6.

5.2. Scenario Tree

To represent a stochastic process, it is normally approximated and predicted by a finite set of values. A scenario tree is an abstract presentation of a stochastic process. It reveals the varying information on uncertain variables during a period of time. A two-stage scenario tree, as an example of a multi-stage scenario tree, is illustrated in Figure 5-1. Generally, a scenario tree comprises nodes and paths. The dark spots in the tree in Figure 5-1 represent the nodes, the nodes show the states of the stochastic variable at the particular instant of time. The blue lines in Figure 5-1 between the spots are the paths between the nodes at different stages. The paths in a scenarios tree between nodes characterize various realization of the stochastic process. Thus, every path in the scenario tree stands for a scenario. Each path has its own probability of occurrence, which represents the probability of one scenario. Furthermore, the sum of the probabilities of all the paths connected to one node at the previous stage equals to one.

With nodes at different stages, it becomes a multi-stage scenario tree. The multi-stage scenario tree can be applied as input into a decision making process, which forms a multi-stage stochastic programming problem. Optimal decisions of the stochastic programming problem are made at every stage corresponding to the multi-stage scenario tree, and the decisions will be available at each node in the scenario tree. Every node at the previous stage is the 'ancestor' of all the nodes connected to it at the next stage. The node at the first stage is the root node, it is located at the beginning of the whole decision making procedure. At the first stage, decisions are made before the stochastic process depending on the current information. The example two-stage scenario tree has five scenarios at the second stage in Figure 5-1. Decisions at the second stage are made based on the paths (i.e. scenarios) connecting the nodes, which depend on the realization of the stochastic process. For multi-stage scenario tree, decisions at the stages after the root node are made one stage after another, following the realizations of previous stages.

A two-stage electricity RTP scenario tree, as indicated in Figure 5-1, is constructed in order to adequately characterize information of potential price rates for the future

24 hours. The construction of a two-stage scenario tree for predicting the future RTP has several steps, including scenario generation, scenario reduction, and evaluation. The following sections introduce and illustrate the methods applied to these steps in this research.

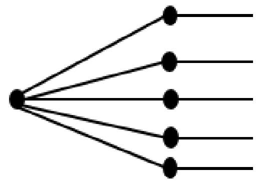


Figure 5-1 A Two-Stage Scenario Tree

5.3. Scenario Generation

Future RTP rates are characterised by potential scenarios with their own probabilities of occurrence. A single RTP scenario can be regarded as one possible energy price realisation. Therefore, potential scenarios are generated to show approximations of the RTP data evolution process and distribution. The marginal distribution and statistical dependence can identify the distribution of a random variable of a stochastic process [113]. To adequately model a stochastic process, a large set of scenarios is normally generated. This is to ensure the generated scenarios sufficiently covers the characterisation of the considered stochastic process.

Major scenario generation methods are reviewed in section 5.3.1, which are moment matching and sampling method. In addition to reviewing scenario generation methods, a detailed procedure of scenario generation used in the research is presented in section 5.3.2, including the results of the generated scenarios.

5.3.1. Brief Overview of Scenario Generation Approaches

Moment matching method is suitable for a stochastic process that is lack of the knowledge of its marginal distribution function. This method uses moments, such as mean, variance, correlation matrix, etc, to describe the probability distribution. The continuous probability distribution is first approximated by representations of the moments of assessed data, and then the moments of the future stochastic process are computed on the basis of the constructed probability distribution. The moments summarise the information enclosed in the assessed data and compute approximate equivalents. If the first few moments of the assessed variables are correctly matched, the following moments can be accurately computed. The calculation results of moments provide a foundation to predict future distributions of scenarios. Common discrete approximation methods are compared to moment matching in [121]. Scenarios generation by using a correlation matrix of moment matching is illustrated in [122]. One problem of moment matching method is it cannot guarantee convergence, which will lead to instability or bias. Furthermore, the convergence problem may not be solved with increasing scenarios numbers [123].

Sampling method samples values based on an underlying stochastic process with a known distribution. The sampling method can be used for univariate and multivariate random variables. If multivariate variables are considered, every signal univariate component can be sampled separately and combined afterwards [123]. One common approach of sampling method is Monte Carlo sampling [124], which is able to generate a random sequence of an independent term under a given distribution and constructing samples by proper transformation with the random independent term. Importance sampling works if the distribution of sampling is restricted to a proportional range of values [125]. When employing the sampling method to generate scenarios, it typically requires a large number of scenarios. This is because a small number of generated scenarios may not be adequate to represent the underlying stochastic process.

5.3.2. Scenarios Generation Using ARMA Time Series Model

As mentioned above, the marginal distribution and statistical dependence are the two key aspects that identify the distribution of the random variable in a stochastic process. In an ARMA model, i) the random variable is the error term, and the error term follows Gaussian distribution, the behaviour (i.e. marginal distribution) of the stochastic process (the RTP rates) therefore can be modelled with Gaussian distribution, and ii) its mean value and variance are independent of time t (i.e. statistical dependence) [113].

With these two advantages, ARMA can simplify the determination of the probability structure of a stochastic process. In addition, since an ARMA (4, 4) time series model is used for forecasting future RTP prices in Chapter 4, the ARMA (4,4) model will be used in the research to generate scenarios. Additional clustering and scenario selection step will be illustrated in the scenario reduction section.

ARMA time series model has an uncorrelated error term ε_t with zero mean and variance of one, which follows the Gaussian distribution. Potential RTP scenarios are generated by means of sampling the distribution of the error term in the ARMA (4, 4) model. As indicated in Table 4-3 of Chapter 4, the error term follows a Gaussian distribution with zero mean value and constant variance 0.0016. Detailed steps of generating scenarios are presented as a flow chart in Figure 5-2.

Before the start of the scenario generation process, the time period and the number of scenarios are defined first. The sampling process randomly generates the error term ε_t at each time step t. A real-time price rate at time t of a scenario is obtained by means of calculation through the ARMA (4, 4) model. The scenario calculation repeats, and one scenario is acquired until the time step t reaches the end of the pre-defined scenario time horizon. After one scenario is generated, the number counter of scenarios will be updated and the sampling process repeats. The iterative scenario generation procedure continues until the number of scenarios generated meets the pre-described scenario numbers. Therefore, the random variation of the error term ε_t formulates scenarios by means of sampling its distribution.

The results of the scenarios generated through the ARMA (4, 4) model is presented in Figure 5-3 and Figure 5-4. One thousand potential future RTP scenarios are generated for a duration of 24 hours in Figure 5-3. Since the original PJM energy pricing data is transformed to achieve stationarity through applying logarithm transformation, the future values of electricity price scenarios in Figure 5-4 are in the logged form. It can be observed that there are a certain number of 'extreme' scenarios generated during the procedure with a relatively deep trough and high peak. Nevertheless, a major amount of the generated scenarios share a similar trend. Probabilities of occurrence of the one thousand generated scenarios are equally distributed, which means a single scenario has a probability of occurrence of 0.001 (= 1/1000). To establish a scenario tree, considering the diversity among the scenarios generated, necessary scenario reduction process need to be employed to reduce/select the scenarios that can represent and characterise the stochastic process.

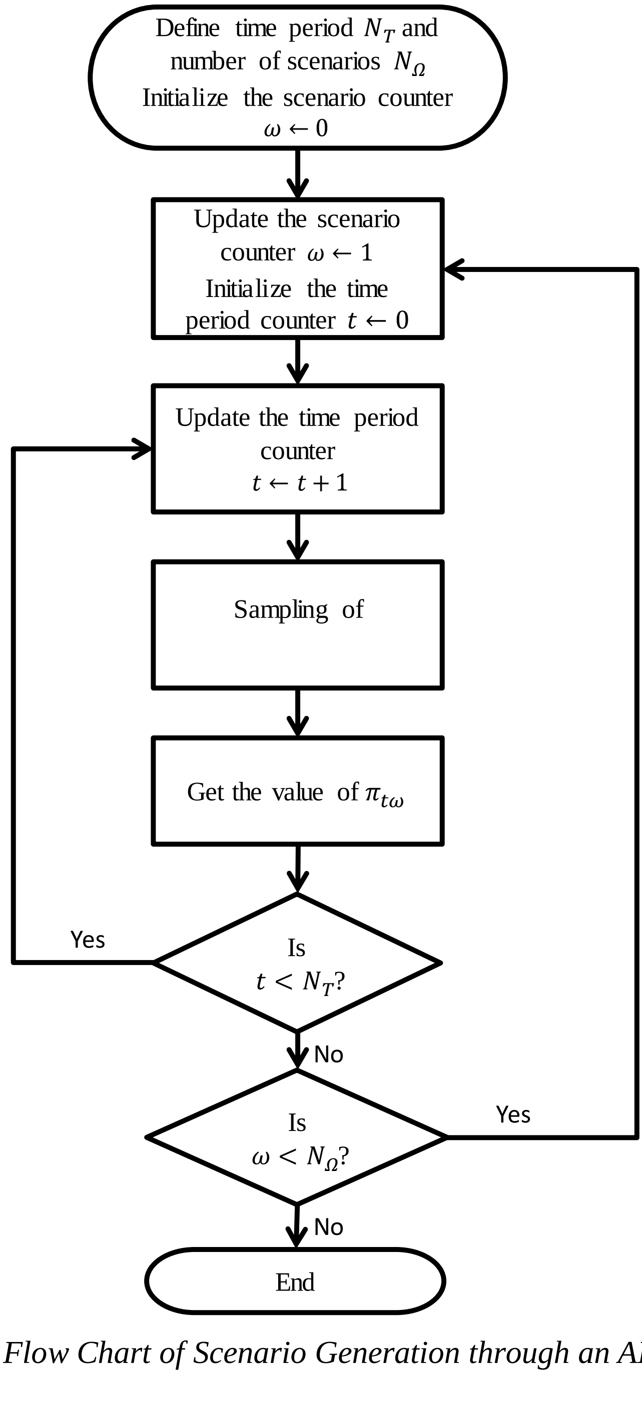


Figure 5-2 Flow Chart of Scenario Generation through an ARMA Model

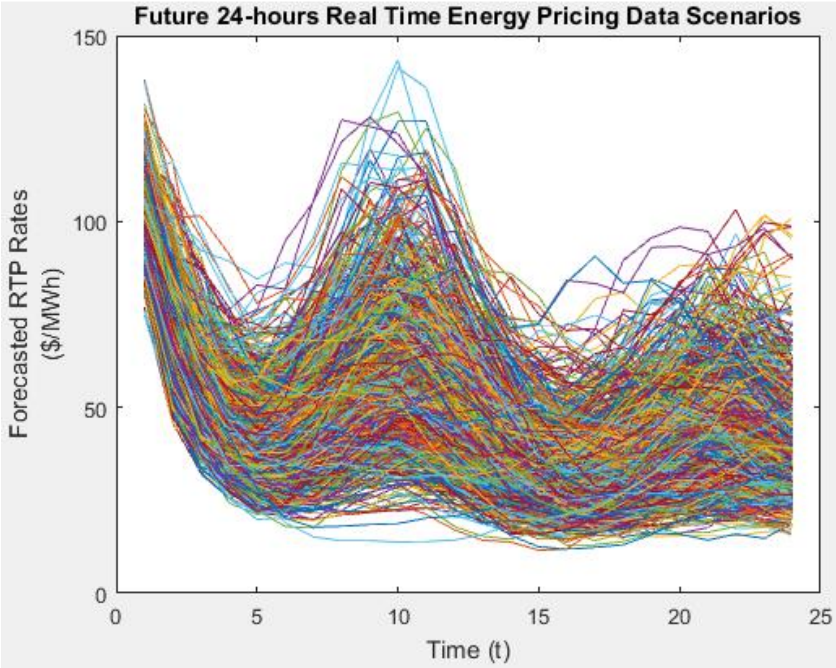


Figure 5-3 1000 Scenarios for Future 24 Hours Energy RTP Rates

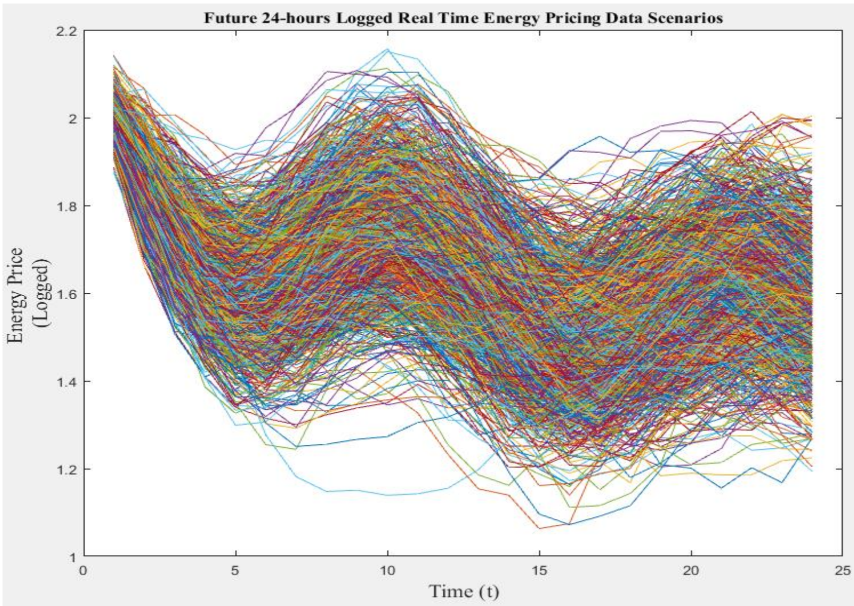


Figure 5-4 1000 Scenarios for Future 24 Hours (logged) Energy RTP Rates

5.4. Scenario Reduction

One thousand scenarios of future RTP is generated based on a sampling process of the ARMA (4, 4) time series model. Repeated sampling of the error term of the time series model is performed to generated scenarios, and a large number (i.e. one thousand) scenarios are generated. This will lead to increased computation burden of the decision making procedure, and acquiring the potential optimal solutions of the developed scheduling tool will be time-consuming. Therefore, it is crucial for stochastic programming problems to obtain a small number of scenarios that can approximate and represent the original random stochastic process. An essential procedure of scenario reduction is carried out to reduce the size of generated scenarios and to decrease the computation burden of the stochastic programming model.

One of the aims of scenarios reduction techniques is to reduce the size of the generated scenarios. While more importantly, the reduced scenarios set should contain characteristics and information close to the original stochastic process. The reduced set of scenarios are selected into the scenario tree as representative scenarios. It is decided that five out of the one thousand generated scenarios will be selected to present the future RTP trend, and the five reduced scenario set will be included in the two-stage scenario tree. Two categories of scenario reduction methods are applied to downsize the generated one thousand scenarios, which are the heuristic algorithm and clustering methods. The heuristic algorithm is based on the probability distance between each scenario, while the clustering techniques distribute scenarios into a pre-defined number of groups. The heuristic algorithm applied in the research is Kantorovich forward selection. The clustering techniques employed are K-Means centroids, K-Means 'local' maximal average local distance, and K-Means 'global' maximal average local distance. Among this, the K-Means 'local' maximal average local distance and K-Means 'global' maximal average local distance methods are published recently in [120]. The techniques are explained in the following sections, and the results of reduced sets are illustrated together with the recomputed probability of occurrence, and these four scenario reduction methods are evaluated in section 5.5.

5.4.1. Scenario Reduction Based on Probability Distance

A probability distance [126] measures how far it is between two scenarios that belong to the same random data process. The Kantorovich distance is normally applied for calculating distances between the probability distribution of Q and that of the reduced set Q_s, its mathematical formation [117, 127] is expressed as,

$$D_k(\mathrm{Q},\mathrm{Q}_s) = \min\left\{\begin{array}{ll} \sum_{\varpi=1}^{\Omega}\sum_{\varpi_s=1}^{\Omega_s} c(\omega,\omega_s)\eta(\omega,\omega_s)\colon \eta(\omega,\omega_s) \geq 0, & \\ \sum_{\varpi_s=1}^{\Omega_s} \eta(\omega,\omega_s) = \mathrm{P}_\omega, \sum_{\varpi=1}^{\Omega} \eta(\omega,\omega_s) = \mathrm{P}'_\omega & \end{array} \forall\omega,\omega_s\right\} \qquad (5-1)$$

. Ω and Ω_s refer to the generated scenarios set and reduced set, respectively. P_ω and P'_ω correspond to the probabilities of the scenarios ω and ω_s in the sets Ω and Ω_s. $c(\omega,\omega_s)$ measures the distance between all the scenarios in the initial set, it is normally called as a cost function. Thus, $c(\omega,\omega_s)$ is a symmetric, nonnegative function. The formulation of $c(\omega,\omega_s)$ is presented as,

$$c(\omega,\omega_s) = \sum_{t=1}^{\mathrm{T}} \|\omega_t - \omega_{st}\|, \qquad \forall t = 1,\dots,T \qquad (5-2)$$

. The $\|.\|$ is the norm operator. It is worthwhile mentioning that the D_k can only be called as Kantorovich distance if the cost function is calculated by a norm. As a result, Kantorovich distance calculates the optimal value between specified probability distributions Q and Q_s.

There are two scenario reduction algorithms proposed in [117, 126, 128] based on the Kantorovich distance, which are forward selection algorithm and backward reduction algorithm. These two algorithms are illustrated in Figure 5-5 [126] and Figure 5-6 [126]. The forward selection algorithm starts from an empty set of reduced scenario. It selects scenarios with minimal Kantorovich distance between the original scenario set and reduced subset. Therefore, the first selected scenarios would always be the average scenario with an average distance to the other scenarios in the original generated set. As showed in Figure 5-5, the 1st, 2nd, and 3rd scenarios are selected based on minimum distance from five scenarios. The backward reduction algorithm begins with the original generated set of scenarios, and it deletes scenarios until the number of scenarios remained reaches the pre-specified number of reduced scenarios. The deletion of 1st and 2nd scenario among five scenarios by means of backward reduction algorithm is presented in Figure 5-6. It can be observed from both Figure 5-5 and Figure 5-6 that three resulted scenarios contained in the reduced set are the same through applying forward selection and backward reduction algorithms.

Based on the findings of [115], the heuristic forward selection algorithm is recommended if the number of scenarios in the reduced set is smaller than ¼ of that in the original set, since the running time of fast forward selection algorithm is smaller. As mentioned above, the one thousand generated future RTP scenarios are aimed to be reduced to five, the forward selection algorithm is therefore used to reduce the number of scenarios.

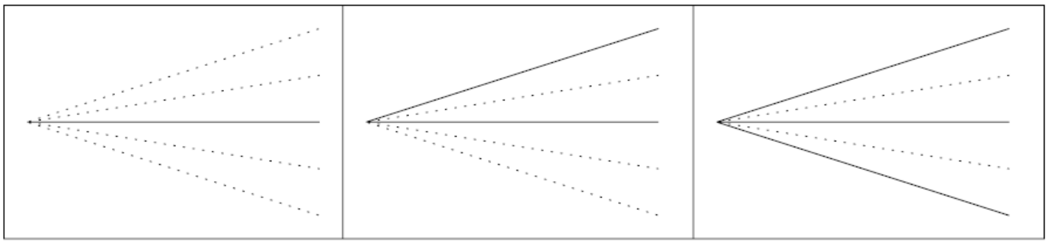


Figure 5-5 Illustration of Forward Selection Algorithm [126]

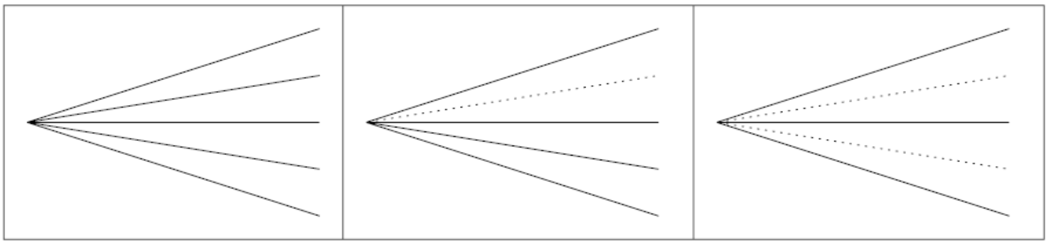


Figure 5-6 Illustration of Backward Reduction Algorithm [126]

5.4.1.1. Kantorovich Forward Selection Algorithm

As given in [127] and based on *Theorem 3* in [117], with Ω and Ω_s refer to the generated scenarios set and reduced set, respectively, and $\Omega \subset \Omega_s$. The representation of the Kantorovich distance can be obtained as,

$$D_k(\mathrm{Q}, \mathrm{Q}_s) = \sum_{\varpi \in \Omega \backslash \Omega_s} \mathrm{P}_\omega \min_{\varpi_s \in \Omega_s} c(\omega, \omega_s) \qquad (5-3)$$

. This equation will be used to calculate the Kantorovich distance between energy pricing scenarios, and forward selection scenario reduction will be based on the computation results of the Kantorovich distance.

The steps of Kantorovich forward selection algorithm are detailed below:

- *Step 0* Start with an empty reduced scenario subset,
- *Step 1a)* Calculate the distance between each pair of scenarios, using the $c(\cdot)$ in $(5-2)$;
- *Step 1b)* Calculate the Kantorovich distance between each pair of scenarios, using the simplified $D_k(\cdot)$in $(5-3)$;
- *Step 1c)* Select the first scenario with the minimum Kantorovich distance obtained in *Step 1b)* through

$$\omega_1 = \arg\left\{\min_{\omega_s \in \Omega} \sum_{\omega \in \Omega} P_\omega c(\omega, \omega_s)\right\} \qquad (5-4)$$

  , and include the selected scenario in the reduced subset. The first selected scenario is regarded as the average scenario, which has an average distance to all the other scenarios in the original generated set,

- *Step ia)* Calculate the distance between each pair of the remaining scenarios in the original generated set, and distance between the scenarios in the reduced set and that in the original set, using the $c(\cdot)$ in $(5-2)$;
- *Step ib)* Calculate the Kantorovich distance between each pair of remaining scenarios in the original generated set, using the simplified $D_k(\cdot)$in $(5-3)$;
- *Step ic)* Select the scenario with the minimum Kantorovich distance to all the scenarios, including the selected set and the scenarios remaining in the original set, by

$$\omega_i = \arg\left\{ \min_{\omega_s \in \Omega_r^{[i-1]}} \sum_{\omega \in \Omega_r^{[i-1]} \backslash \{\omega_s\}} P_\omega \min_{\omega_s' \in \Omega_s^{[i-1]} \cup \{\omega\}} c(\omega, \omega_s') \right\} \quad (5-5)$$

, where Ω_r is the set of remaining scenarios in the initial generated set, and Ω_s is the selected scenario set. The *Step i) (i.e. Step ia) – Step ic))* repeats until the number of scenarios in the selected set reaches the pre-determined value,

- *Step i+1)* Probability of occurrence of each reduced scenario will be recomputed by grouping the nearest scenarios, which are not selected and remained in the initial generated set, with the selected scenarios in the reduced set. The optimal probability redistribution follows

$$\mathrm{P}_\omega^* = P_\omega + \sum_{\omega_s \in r(\omega)} P_{\omega_s} \quad (5-6)$$

to form the new probability of occurrence for the reduced scenario subset. The $r(\omega)$ refers to the set of non-selected scenarios in the original generated set with minimum distance $c(\cdot)$ to the selected scenarios. Therefore, the new probability of selected scenarios equals to the sum of its own original probability and all the probabilities of the remaining scenarios $r(\omega)$ close to it according to the distance computed in $(5-2)$.

Results of five scenarios selected from the one thousand generated scenarios by means of the forward selection algorithm are given in Figure 5-7. The starting point of the RTP scenario is high due to the last value of the historical PJM energy pricing data is high. It can be observed from Figure 5-7 that all the five scenarios selected follow a similar trend over time. The probability of occurrence of selected scenarios set is calculated through the optimal redistribution of probability in equation $(5-6)$, with the new probabilities of selected scenarios equal to the sum of its original probability of occurrence and the probability of all the adjacent scenarios remaining in the initial set. Therefore, the probability of occurrence of scenario 1 (yellow) is 25.1%, scenario 2 (red) is 18.9%, scenario 3 (purple) is 21.5%, scenario 4 (blue) is 17.7%, and scenario 5 (green) is 16.8%.

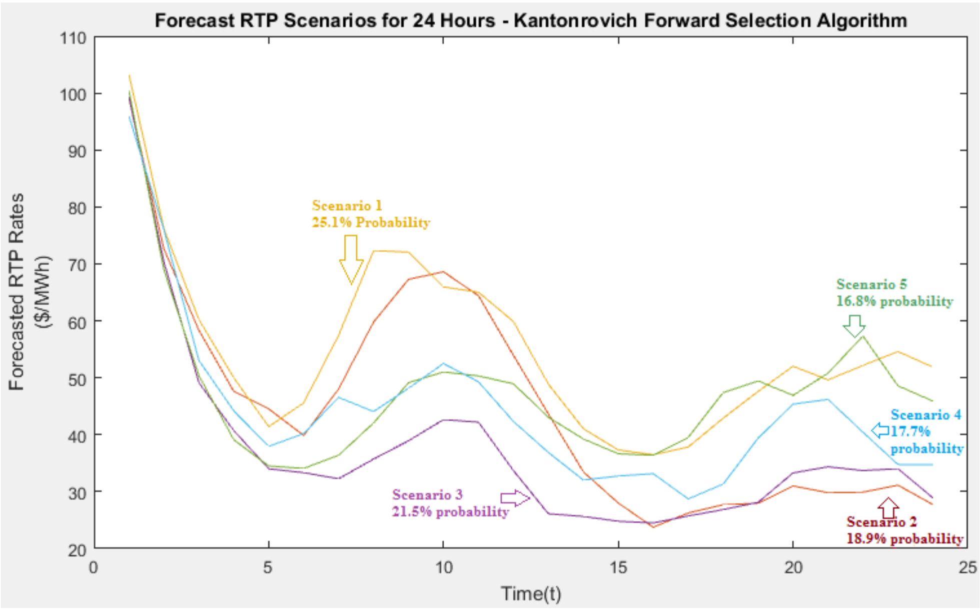


Figure 5-7 Scenario Reduction Results through Forward Selection Algorithm

5.4.2. Scenario Reduction Based on Clustering

Another category of scenario reduction techniques is clustering. The aim of clustering method is to bundle similar scenarios in the initial set of generated scenarios. A prescribed number of groups are formed through bundling, and a representative scenario is selected out from each cluster.

The K-Means algorithm introduced by Lloyds in [129] is widely used in clustering, it bundles the objects into the same cluster by means of minimizing the average distance between them. The algorithm starts with randomly chosen centres of the clusters, the data closer to a centre will be included in the cluster where the centre sits. After the clustering process finishes, the centre of each group is recalculated and reassigned to ensure it is the centre of each cluster. The assignment of data into groups and reallocation of centres are repeated until no more data is assigned to a different cluster and the centres stay the same. Improvements of the K-Means algorithm are proposed in [118], called K-Means++. The major steps of the K-Means++ algorithm are similar to the K-Means, but it introduced an advanced way for choosing the initial centres of clusters. The initial centroid is chosen randomly from the object dataset. The second centroid is chosen with a specified probability which is calculated based on the distances between all the data. The centroid selection procedure iterates until the prescribed number of clusters is met. After the centroids are chosen, the same steps on the clustering and re-computation of the centre in K-Means algorithm are repeated until the system is stable.

K-Means++ algorithm is employed in the research to cluster the originally generated scenarios. Since a representative scenario from each cluster is selected in order to form the reduced set of scenarios, the amount of clusters is equal to the prescribed number of scenarios in the reduced set. Three ways of choosing representative scenarios in each cluster based on K-Means++ algorithm are applied to the one thousand generated scenarios, which are K-Means centroids algorithm [119], and K-Means 'local' maximal average distances algorithm [120], and K-Means 'global' maximal average distances algorithm [120]. The resulting reduced scenario sets of the three methods are discussed.

5.4.2.1. K-Means Centroids

The K-Means centroids method first clusters the data into a prescribed number of groups. Scenarios are chosen out from each cluster by using the centroid of each group, due to the centroid of each cluster has an average distance to the other scenario in it. The step by step K-Means centroids method is illustrated below:

- *Step 1a)* Choose initial centroids according to K-Means ++,
- *Step 1b)* Clustering scenarios into groups by calculating the distance between each pair of them, calculate the distance $c(\cdot)$ in $(5-2)$,
- *Step i)* Evaluate the centroids of each group, an average scenario is computed in each cluster, and reassign the scenarios into groups. A certain number of scenarios may be assigned to different clusters. Repeat the step until there is no (or a very small number of) scenarios are assigned to different groups,
- *Step i+1)* Select representative scenarios. For the K-Means centroids algorithm, the centroid of each cluster is chosen and included in the reduced subset,

- *Step i+2)* Redistribution of probability. For the K-Means centroids algorithm, since one scenario is selected out from each cluster, the new probability of selected scenarios equal to the sum of probabilities of scenarios belonging to the relevant cluster. The new probability of the selected scenarios can be calculated by

$$\mathrm{P}_{\omega_s} = \sum_{\omega_c \in \Omega_c} \mathrm{P}_{\omega_c} \qquad (5-7)$$

, with $\omega_s \in \Omega_c$ and $\omega_c \in \Omega_c$. Ω_c refers to the set of scenarios in one cluster.

The reduction results by selecting centroids as the representative scenarios from clusters are given in Figure 5-8. It is noted that the trends of the five selected scenarios through K-Means centroids algorithm is similar to that of the forward selection algorithm. However, the values of K-Means centroids selected scenarios are more volatile when comparing to that of the forward selection method. The redistributed probability of occurrence of the selected scenarios, through the K-Means centroids method, is computed as the probability of the clusters that the scenario is selected from. As a result, as indicated in Figure 5-8, scenario 1 (purple) has a probability of occurrence of 11.7%, scenario 2 (yellow) of 11.7%, scenario 3 (red) of 22.7%, scenario 4 (blue) of 26.8%, and scenario 5 (green) of 27.1%.

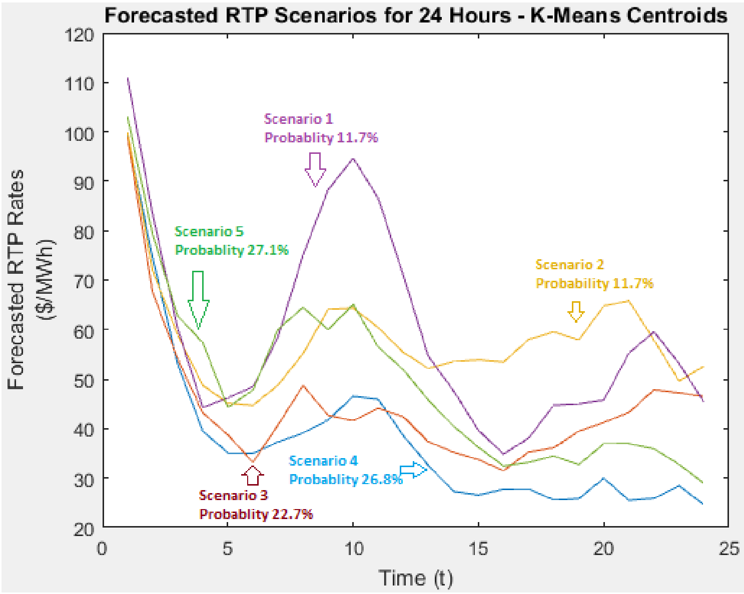


Figure 5-8 Scenario Reduction Results through K-Means Centroids Algorithm

5.4.2.2. K-Means 'Local' Maximal Average Distances

The K-Means 'local' maximal average distance clusters the generated scenarios into groups as well, but the selection of scenarios is different with the K-Means centroids algorithm. The 'local' maximal average distance calculates the average distance between each scenario in the same cluster, and the one with the maximum distance to the other in the clusters will be chosen. The steps to selected scenarios by means of 'Local' maximal average distance is similar to that of K-Means centroids algorithm except for the scenario selection procedure, which is introduced as below:

- *Step 1a)* Choose initial centroids according to K-Means ++,
- *Step 1b)* Clustering scenarios into groups by calculating the distance between each pair of them, calculate the distance $c(\cdot)$ in $(5-2)$,
- *Step i)* Evaluate the centroids of each group, an average scenario is computed in each cluster, and reassign the scenarios into groups. A certain number of scenarios may be assigned to different clusters. Repeat the step until there is no (or a very small number of) scenarios are assigned to different groups,
- *Step i+1)* Select representative scenarios. For K-Means 'local' maximal average distance algorithm, one scenario is selected from one cluster with the maximum average distance to others in the same cluster. The scenarios are selected by

$$\omega_s \in \arg\left\{\max_{\omega_s \in \Omega_c} \sum_{\omega_c \in \Omega_c} P_{\omega_c}\, c(\omega_s, \omega_c)\right\} \qquad (5-8),$$

Step i+2) Redistribution of probability. For K-Means 'local' maximal average distance algorithm, similar to the K-Means centroid method, since one scenario is selected out from each cluster, the new probability of selected scenarios equal to the sum of probabilities of scenarios belonging to the relevant cluster. The new probability of the selected scenarios can be calculated by equation $(5-7)$.

Scenario selection results of K-Means 'local' maximal average distance algorithm is presented in Figure 5-9. Each of the representative scenarios chosen by 'local' maximal average distance has completely different behaviours over time, when comparing the forward selection algorithm results in Figure 5-7 and centroids method results in Figure 5-8. Because the scenarios reduced by the K-Means 'local' maximal average distance are selected from the same clusters as the K-Means centroids method, the calculated probabilities of occurrence of the reduced scenarios resulting from the 'local' maximal distance are the same as that of K-Means centroids. However, the K-Means 'local' maximal average distance selects completely different scenarios from the cluster, as it searches for the scenario has the maximum distance to the other ones in the same cluster. Thus, the probability of occurrence of scenario 1 (purple) is 11.7%, scenario 2 (yellow) is 11.7%, scenario 3 (red) is 22.7%, scenario 4 (blue) is 26.8%, and scenario 5 (green) is 27.1%.

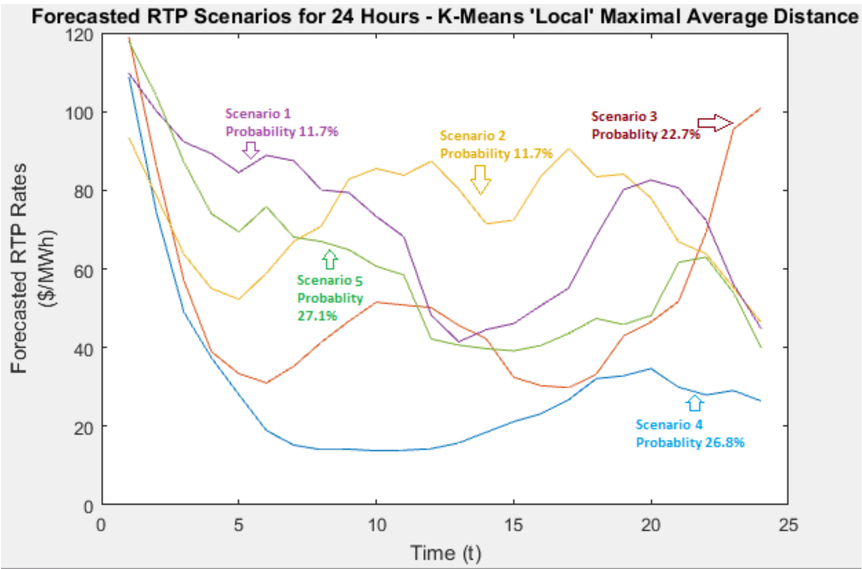


Figure 5-9 Scenario Reduction Results through K-Means 'Local' Maximal Average Distance Algorithm

5.4.2.3. K-Means 'Global' Maximal Average Distances

This algorithm chooses scenarios by means of 'global' maximal average distances. The average distances between scenarios are computed in a similar manner as in the K-Means 'local' maximal average distance algorithm, but it finds a prescribed number of scenarios by computing the distances between all the scenarios in the initially generated scenario set ignoring the cluster boundary.

- *Step 1a)* Choose initial centroids according to K-Means ++,
- *Step 1b)* Clustering scenarios into groups by calculating the distance between each pair of them, calculate the distance $c(\cdot)$ in $(5-2)$,
- *Step i)* Evaluate the centroids of each group, an average scenario is computed in each cluster, and reassign the scenarios into groups. A certain number of scenarios may be assigned to different clusters. Repeat the step until there is no (or a very small number of) scenarios are assigned to different groups,
- *Step i+1)* Select representative scenarios. For K-Means 'global' maximal average distance algorithm, one scenario is selected from one cluster with the maximum average distance to others without considering cluster assignments. The scenarios are selected through

$$\omega_s \in \arg\left\{\max_{\omega_s \in \Omega} \sum_{\omega_c \in \Omega} P_{\omega_c}\, c(\omega_s, \omega_c)\right\} \qquad (5-9)$$

,

- *Step i+2)* Redistribution of probability. For K-Means 'global' maximal average distance algorithm, the new probabilities of selected scenarios are computed based on the optimal probability distribution in equation $(5-6)$, as the selection of scenarios is not limited in clusters.

Selection results of scenarios by means of K-Means 'global' maximal average distances are given in Figure 5-10. The five selected scenarios all have higher rates during the morning time at around 10 am, and the overall trend of the five scenarios are similar. Although the trend of the five scenarios selected through K-Means 'global' maximal average distances is similar to that of the forward selection algorithm in Figure 5-7, the scenarios selected in Figure 5-10 have larger oscillations (i.e. the differences between the highest and lowest values). This is because K-Means 'global' maximal average distances method selects completely different scenarios, which are the most extreme ones among the one thousand generated scenarios. Scenario 2 (blue) and scenario 4 (red) have a smaller peak at around 9 – 10 pm. The probability of occurrence is calculated by grouping the nearest scenarios ignoring the boundaries of clusters. Scenario 1 (purple) has a probability of occurrence of 0.6%, scenario 2 (blue) of 2.5%, scenario 3 (yellow) of 38.8%, scenario 4 (red) of 22.5%, and scenario 5 (green) of 35.6%. It can be observed that extreme scenarios with very low probabilities of occurrence are selected using the K-Means 'global' maximal average distance method.

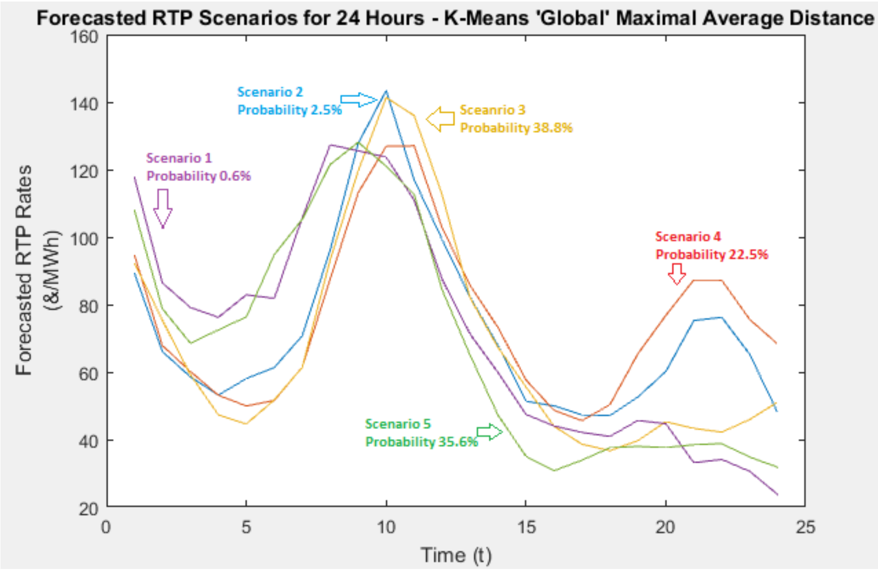


Figure 5-10 Scenario Reduction Results through K-Means 'Global' Maximal Average Distance Algorithm

5.4.3. Comparison between Scenario Reduction Methods

The Kantorovich forward selection algorithm selects a scenario at each iteration step through calculating the Kantorovich distance between each scenario in the initial set. The K-means clustering algorithms select the centroids and bundle all the scenarios into a prescribed number of clusters. Three scenario selection algorithms based on clustering are applied to scenario reduction, one is to choose the centroids, the other two select scenarios out on the basis of the distance between scenarios within/without clusters. Since the 'local' and 'global' maximal average distances algorithms proposed in [120] calculates the maximum average distances between scenarios within/without clusters boundaries, these two algorithms are very likely to select scenarios with the most drastic behaviour among the original generated one thousand scenarios. This can also be reflected in the selected scenarios in both Figure 5-9 and Figure 5-10.

In addition, it is worthwhile mentioning that the configuration of the prescribed number of clusters needs to be discreet as it may result in unstable clustering due to certain scenarios can be grouped into either two of all the clusters. A silhouette plot [130] of five clusters is produced during the scenario reduction process, and it is presented in Figure 5-11. The one thousand generated scenarios are divided into five clusters based on the K-Means clustering. The silhouette plot is a graphical aid, which is computed based on the distance between 1) one scenario and other scenarios within the same cluster and, 2) scenarios in its own and adjacent clusters. Values calculated in the silhouette plot ranges from -1 to 1, which indicate if the scenarios are distinct from that in neighbouring clusters. 1 implies scenarios that are very distinct, and -1 indicates scenarios that are probably assigned to the wrong cluster. It can be observed from Figure 5-11 that the majority of the one thousand generated scenarios are distinct from each other and they can be assigned into corresponding clusters. While there are few scenarios in cluster 3 and 4 have silhouette values of around -0.25, which means there exist a few scenarios that are not distinct from one cluster to the other. Nevertheless, the overall silhouette plot indicates the generated one thousand scenarios can be assigned into clusters and no unstable clustering occurred.

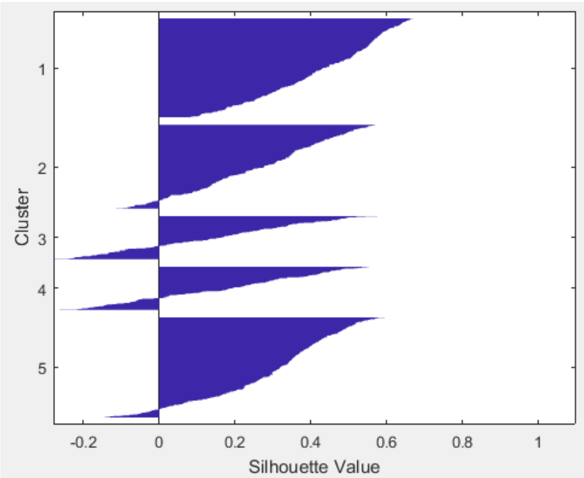


Figure 5-11 Silhouette Plot of Five Clusters Based on K-Means Clustering

On the computation speed, K-means clustering with centroids is the fastest among the four methods. The speed and burden of the Kantorovich forward selection algorithm increase with the number of scenarios needed to be selected. The same situation applies to the clustering algorithms with ‘local’ and ‘global’ maximal average distance.

The quality of scenario trees containing all the reduced set of scenarios is evaluated by inputting them into the basic customer-centred scheduling tool in the next section. Several subsets with different cardinalities of reduced scenarios are evaluated in order to give a comprehensive evaluation.

5.5. Evaluation of Scenario Trees

At this stage, four two-stage scenario tree is established with the reduced scenario subsets resulting from the above scenario generation and reduction steps. The reduced scenario subsets are the paths between the root node and second stage nodes in Figure 5-1, where every single scenario in one subset has its own probability of occurrence.

The aim of using a scenario tree is to approximate a stochastic process. A good scenario tree should contain sufficient information close to the stochastic process. Therefore, it is vital to evaluate the qualities of the scenario trees developed for representing future stochastic electricity RTP rates.

The quality of a scenario tree is tested through several aspects in [123], and stability is the minimum requirement for testing the quality. It requires (approximately) the same optimal value of the objective function in an optimization problem, when using the scenario trees as input into the problem. To test the stability, it is required that all the scenario trees tested in the optimization problems and compared should result from the same input, which refers to the same scenario generation procedure and the same historical data in this research. Furthermore, the structure of the scenario trees also needs to be examined to see if they have the same number of nodes and paths. Therefore, the four scenario trees, resulting from the above scenarios reduction algorithms, are comparable and evaluable through the in-sample stability.

The reduced scenario subsets of the scenario trees are input into the basic scheduling tool, and the tool outputs optimized values of consumers' energy bills. The House B model is used to test stability. The reduced subsets of forecasted 24-hours RTP scenarios are performed as the paths connecting the root node at the first stage and the second stage nodes in the two-stage RTP scenario tree. Various cardinalities of reduced scenario sets, i.e. different number of scenarios in the reduced scenario sets, are tested into the tool and the optimal solutions are compared by the mean values and standard deviations. Results of the in-sample stability test are presented in Table 5-1. The Kantorovich forward selection algorithm and K-means Centroids share similar mean optimal objective value and standard deviation no matter how many scenarios are selected out from the initial generated set. Differences, in the mean and standard deviation of the optimal solution values, exist between the former two algorithms and the latter two algorithms based on the 'local' and 'global' maximal average distances. The aim of the 'local' and 'global' maximal average distances algorithms is to delete all the less significant scenarios to represent the original one [120]. While the forward selection and K-Means centroids algorithms quantify the closeness of scenarios in order to represent the originally generated scenarios.

Since testing the stability requires the similar optimal value of the objective function in an optimization problem, the Kantorovich forward selection and K-Means centroids algorithm can be used to form representative RTP scenario trees. As discussed in section 5.4.3, the speed of K-Means centroid algorithm is faster than the forward selection method. However, there might exist scenarios that can be clustered into either two groups during the K-Means clustering. This will influence the probability of occurrence of the selected scenarios. Therefore, the Kantorovich fast forward selection algorithm is preferred in this research to form the two-stage RTP scenario tree.

It is worthwhile mentioning that not all the scenario generation and reduction algorithms suit in every stochastic process. The decision of choosing scenario generation and reduction techniques should combine the practical model condition with the computational tractability of the algorithms. In addition, the speed of a scenario generation/reduction is not an important criterion, but the closeness between the selected scenario subsets and the original scenarios set. However, if the computation speed of a scenario generation/reduction method is too slow to be useful for its application, the speed should also be considered in that case.

Table 5-1 In-Sample Stability Test Results

Scenario Trees *(resulting from different scenario reduction algorithms)*	Optimal Solution Value	Cardinality of Reduced Scenarios Subset			
		3	5	10	20
Forward Selection Algorithm	Mean value($)	16.79	16.43	16.39	16.53
	Standard Deviation	3.38	2.89	3.27	3.15
K-Means Centroids Algorithm	Mean value($)	16.59	16.55	16.55	16.57
	Standard Deviation	2.72	3.12	3.31	3.06
K-Means ‘Local’ Maximal Average Distance Algorithm	Mean value($)	17.51	16.4	15.18	14.67
	Standard Deviation	6.32	5.77	5.25	3.81
K-Means ‘Global’ Maximal Average Distance Algorithm	Mean value($)	9.07	9.36	12.87	14.75
	Standard Deviation	0.05	0.07	6.53	6.69

5.6. Summary

Following the forecasting of real-time energy pricing in Chapter 4, this chapter has proposed to establish a scenario tree to better forecast the stochastic RTP rates due to its high volatile characteristic.

This chapter has built a two-stage scenario tree with a finite set of possible future RTP scenario. Each scenario has its own corresponding probability of occurrence. By applying a scenario tree, the stochastic RTP rates are revealed gradually with the process of moving to the next stage. The composition, including the nodes and paths, of a multi-stage scenario tree has been reviewed in this chapter. The nodes in a scenario tree refer to when the decisions of stochastic programming are made, and the paths connecting the nodes between two stages are the potential scenarios. This chapter has also illustrated the steps to build the two-stage scenario tree, which are scenario generation, scenario reduction and evaluation of different scenario tree resulting from various scenario generation/reduction algorithms.

Typical scenario generation methods have been reviewed in this chapter, including the methods used in the research. One thousand scenarios have been generated through Monte-Carlo sampling of the error term based on the ARMA (4, 4) time series model acquired in Chapter 4. To downsize the generated one thousand scenarios, different scenario reduction algorithms have been applied. The reduction techniques are Kantorovich forward selection method based on probability distances, K-Means centroids algorithm and K-Means ‘local’ and ‘global’ maximal average distances algorithm based on clustering. Detailed steps of scenario generation and reduction algorithms can be found in section 5.3.2 and section 5.4, including the results of the algorithms. The comparison between different scenario reduction algorithms has been discussed in section 5.4.3.

The last step of building the scenario tree is to evaluate the quality of the trees, which are the results of the scenario generation and reduction steps. The quality of scenario trees is tested through stability, by using the scenario trees as input into the customer-centred scheduling tool. If the objective function values of the scheduling tool are similar, the scenario trees satisfy the stability test. The House B model is used to test stability. Various cardinalities of reduced scenario subsets have been tested into the tool and the optimal solutions have been compared by the mean values and standard deviations. The results of the optimal solutions show that the resulted scenario tree from the forward selection and K-Means centroids algorithm share similar optimal solution value, observed from mean and standard deviation, although the cardinality of the scenario subsets changes. Since the aim of the ‘local’ and ‘global’ maximal average distances algorithms is to keep the most significant scenarios, there have been differences between the optimal solution values of these two algorithms. Therefore, the Kantorovich forward selection and K-Means centroids algorithm can be used to form representative RTP scenario trees. However, considering there might exist scenarios that can be clustered into either two groups during the K-Means clustering, which will impact on the probability of occurrence of the selected scenarios, the Kantorovich fast forward selection algorithm is preferred in this research to form the two-stage RTP scenario tree.

The established two-stage RTP scenario tree will be integrated with the rolling planning technique to produce a stochastic customer-centred scheduling tool. The stochastic scheduling tool will be able to take stochasticity into consideration and better position customers to react to stochastic real-time pricing. The rolling planning technique and the stochastic tool will be introduced in Chapter 6.

Chapter 6
Stochastic Demand Response Scheduling Tool

6.1. Introduction

The power system is facing growing stochasticity nowadays. With the growing stochasticity, better matching of supply and demand becomes one of the challenges of system operation. Thus, more operational flexibility is needed and demand side can provide certain flexibility. RTP can be used as a price-based DSM approach. It has varying rates over time as the rates reflect network conditions. Customers who are willing to respond to RTP can achieve a lower energy bill payment and benefits network operation by providing demand flexibility. A stochastic scheduling tool is proposed in this chapter to enable customers to better respond to stochastic electricity prices.

The stochastic scheduling tool enhances the basic scheduling tool developed in Chapter 3. The scheduling tools employ the customer-centred approach combined with the price-incentive techniques. In contrast to the DLC methods, this customer-centred approach encourages consumers to participate and make their own decisions regarding when and how much they are going to consume the energy in their households. The consumer-based scheduling tool automatically schedules load devices based on consumers' preferences and their daily electricity consumption patterns, without expecting customers to be constantly engaged. Therefore, consumers are taking control of their home devices via the scheduling tool, rather than being remotely switched by network (system) operators/aggregators. This approach may significantly improve customer engagement and consequently increase the energy savings of residential households, if customers seek to improve their energy efficiency and reduce energy waste.

The stochastic scheduling tool enables actively participating consumers to react to the external inflow of electricity price signals automatically, while also taking into consideration stochastic nature of the varying Real-Time Pricing (RTP) tariffs. As mentioned before, the rates of RTP can reflect the energy system conditions. The stochastic scheduling tool shares the same aim with the basic scheduling tool, which is to minimize the expense of end-users' energy consumption while satisfying consumer's electricity usage preferences and their predetermined living patterns. In addition, to account for the stochastic nature of incoming price signals that can be changed close to real time or at a real-time operation, the proposed stochastic scheduling tool employs the two-stage RTP scenario tree developed in Chapter 5 and rolling planning [23] technique. The rolling planning technique divides the planning horizon into equally distributed time intervals. This research improves the application of rolling planning techniques by including scenario trees and involving external decisions. The external decisions here refer to any external inflow price signals coming from the network (system) operator/aggregator side. As a result, the stochastic scheduling tool enables the end-users to respond to operator /aggregators requests but in the condition of satisfying consumers' energy consumption preferences.

The rolling planning technique will be introduced in the following section 0. Based on the introduced rolling planning technique, the combination of the rolling planning technique and scenario trees will be illustrated in section 6.3.1, and formulation of the stochastic scheduling tool will be presented in section 6.3.2. Detailed application steps of the stochastic scheduling tool will be presented in the case study section 6.3.3.1. Finally, the scheduling results of the stochastic scheduling tool are going to be discussed in section 6.3.3.2.

6.2. Rolling Planning

The rolling planning technique is a consecutive dynamic planning approach which allows constructing a plan under uncertainty for a future period of time [23]. It is a planning framework that combines short-term and long-term plans, and it also integrates planning and control. The technique has been applied to production schedule in a material requirement planning system[131, 132], tour passenger handling agency services at airport terminals and airlines [133], unit commitment optimisation with wind generation [134] and etc. The application of rolling planning on passenger handling agency services is illustrated in Figure 6-1 [133].

Rolling planning is defined as an iterative process. Generally, at the beginning of the planning horizon, a plan is designed for a prescribed future time duration, e.g. for T periods, 1, ..., T. The rolling planning starts with the plan for T periods, and it divides the whole planning horizon into equally distributed time intervals ΔT. At the first step, the ΔT period is implemented, and a new plan is generated for period $\Delta T+1, \dots, \Delta T+T$, i.e. the rolling horizon T. As a result of the new planning is proposed, the planning results is rescheduled during period $\Delta T+1, \dots, \Delta T+T$. After that, iterative steps of following ΔT periods are planned until the plan for the whole rolling planning procedure for T periods is finalised along with the planning horizon T. The time interval ΔT slides the planning horizon with iterations [23, 135]. As a result, the crucial part of the development of a rolling planning framework is the consideration of the planning procedure, i.e. how the decision is made and how to relate the decisions made in each planning loop. The planning decision made at the start of each time interval is formulated according to the past planning decisions and currently available information.

Based on the general rolling planning technique described above, there exist certain modifications to the approach. A modified example that illustrates a rolling planning technique application on passenger ground-handling services is presented in Figure 6-1. The planning of tour schedule is conducted for the next 30 days. It can be observed that 7-days ahead is planned during each iteration, which is indicated by black boxes in Figure 6-1. The tour schedule uses rolling planning in a slightly different way, where only first 4 of the 7 days planning results are recorded during each iteration except the first step. The recorded plans are implied through dark grey filled boxes in Figure 6-1. The whole planning procedure ends until the planning horizon of 30 days are covered.

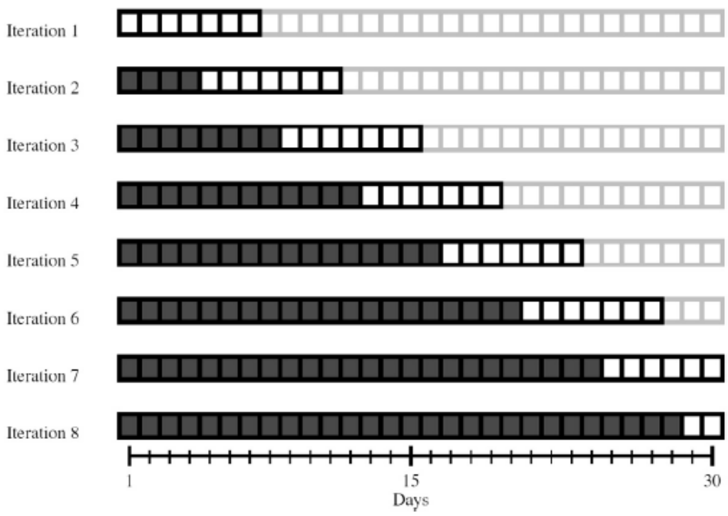


Figure 6-1 Illustration of Rolling Planning Application in Tour Scheduling Agency Services [133]

6.3. Stochastic Demand Response Scheduling Tool

6.3.1. Introduction

The stochastic customer-centred scheduling tool combines the forecasted electricity RTP scenario tree and the dynamic rolling planning technique. By including RTP scenario tree and dynamic planning method, it allows the stochastic tool to do the scheduling and reacting to the uncertainty coming from the changing RTP rates at the same time. Although the RTP rates can reflect power system conditions, e.g. system imbalances and network congestions, the rolling planning procedure also considers external notifications, sent from network (system) operators/aggregators, at the beginning of each planning iteration. This is because

i) shorter term RTP forecasting performs better than long-term price forecasting, this improves prediction results; and

ii) the external notification given by operators/aggregators can also indicate if there is any specific operation request from them to coordinate the consumers' responses, so the stochastic tool can schedule customers to provide certain flexibility and assist network operation.

The application that combines rolling planning and scenario tree in the stochastic scheduling tool is illustrated in Figure 6-2. Dynamic electricity price scenarios are forecasted and established as an input signal into the scheduling tool. In order to represent the stochastic process, a two-stage scenario tree is constructed in each single planning loop. The two-stage RTP scenario tree is built step by step in Chapter 5. One thousand potential future RTP scenarios are generated by sampling of the error term in the ARMA (4, 4) time series model. Detailed steps of fitting the time series model are given in Chapter 4. Scenario reduction algorithms are applied to reduce the number of one thousand generated scenarios to five, which are heuristic algorithm based on probability distances [115-117] and clustering [118-120]. After evaluating the in-sample stability [123] of the scenario tree from the scenario generation and scenario reduction results, the reduced scenario sets of the forward selection algorithm based on probability distance are selected to construct the two-stage scenario tree in Figure 6-2.

A single planning loop covers several hours in the planning horizon. Every single loop in the rolling planning model given in Figure 6-2 covers three hours, which stands for the planning time intervals. The decision made at the start of the whole planning horizon is a 'root decision'. For each planning loop, the decision made at the beginning of a loop is based on gradually revealed information acquired for the random variable, so the realization of the planning decision at each time interval is available at the start of each loop. The planning decision at the beginning of each planning loop is associated with the current information, past data behaviour, and external notifications. The external notifications refer to the signals sent from the network (system) operators/aggregators if there is any specific network operation request from them to coordinate the consumers' responses or to revise the current scheduling decision, based on the latest network conditions. If an external notification is received before the start of a planning loop, the scheduling decision will be altered based on the external notification. The process continues and new planning/scheduling is carried out at each time interval until the whole rolling planning procedure ends.

Rolling planning combines the long term and short term planning into one procedure. The structure of the rolling planning method employed in this research enables active interactions between operators and consumers. By applying the rolling planning method, the stochastic scheduling tool helps active participate consumers to schedule their home appliances by considering potential variation of real-time electricity prices, and if needed, schedule the appliances to assist the network operation.

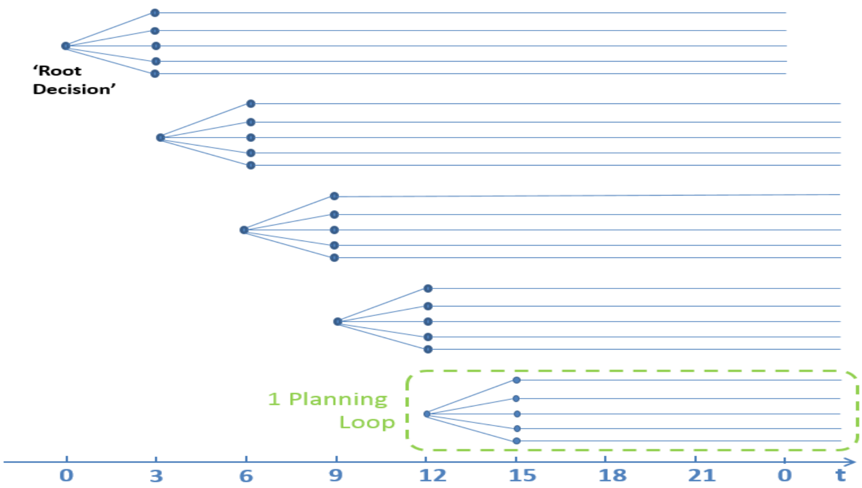


Figure 6-2 Rolling Planning and Scenario Tree in Stochastic Scheduling Tool

6.3.2. Mathematical Formulation

The mathematical formulation of the stochastic scheduling tool are given below. Since the stochastic scheduling tool enhances the basic scheduling tool developed in Chapter 3, the formulation of the stochastic tool are enriched based on the scheduling tool. The objective of the stochastic scheduling tool is to minimize consumers' bill payments over a given period of time as well. The stochastic scheduling tool determines the statuses of the devices in the houses. At the beginning of each planning loop, the status of each device is updated based on the scheduling results in previous loops. The stochastic scheduling tool will be applied to House B, House D, and House G (the same house models in section 3.2.3.2, section 3.2.3.4 and section 3.2.3.7 in Chapter 3).

6.3.2.1. House B

House B contains seven home appliances and one energy storage device. The seven home appliances include devices with different flexibility levels, which are high, medium, and low flexibility home devices. High flexibility devices can be easily shifted to run at another time, while low flexibility appliances have to be scheduled when it is needed.

Objective function:

$$\underset{t}{Minimise}\, COST = \sum_{t=1}^{T} \{P(t) * \pi(t)\} \tag{6-1}$$

Subject to**:**

$$\tau = \mathrm{mt} \qquad \tau \in \{1, \dots, T\},\ t \in \{1, \dots T\},\ \forall \tau, \forall \mathrm{m}, \forall t \tag{6-2}$$

$$\mathrm{N}\tau = T \qquad \forall \tau, \forall \mathrm{n} \in \{0, \dots, \mathrm{N}\} \tag{6-3}$$

$$P(t) = \{\sum_{i=1}^{I} P_i u_i(t)\} + P_{s.char.grid}(t) - P_{s.dischar.app}(t) \qquad \forall i, \forall t, \forall s \tag{6-4}$$

$$P_{min}(t) \le P(t) \le P_{max}(t) \qquad \forall t \tag{6-5}$$

$$T_{i.\ ON} \ge \begin{cases} T_{i.\ op} & \\ T_{i.\ op} - t_{ON.ini} & if\ u_{i.ini}(t=0) = 1 \end{cases} \qquad \forall i, \forall t \tag{6-6}$$

$$T_{i.\ ON} \ge \begin{cases} T_{i.\ op} & \\ T_{i.\ op} - t_{ON.ini.n\tau} & if\ u_{i.ini}(t=n\tau) = 1 \end{cases} \qquad \forall i, \forall \tau, \forall t, \forall \mathrm{n} \tag{6-7}$$

$$T_{i.\ OFF} \leq \begin{cases} T_{i.\ off}^{max} \\ T_{i.\ off}^{max} + t_{ON.ini} & if\ u_{i.ini}(t=0)=0 \end{cases} \qquad \forall i, \forall t \qquad (6\text{-}8)$$

$$T_{i.\ OFF} \leq \begin{cases} T_{i.\ off}^{max} \\ T_{i.\ off}^{max} + t_{ON.ini.n\tau} & if\ u_{i.ini}(t=n\tau)=0 \end{cases} \quad \forall i, \forall \mathrm{\tau}, \forall t, \forall \mathrm{n} \qquad (6\text{-}9)$$

$$U_{i\ \ ON.n\tau} = 1^{\mathrm{n\tau}} *\ u_i(t) \qquad \forall \mathrm{n}, \forall \mathrm{\tau}, \forall i, \forall t \qquad (6\text{-}10)$$

$$U_{i\ \ ON} = 1^{T} *\ u_i(t) \qquad \forall i, \forall t \qquad (6\text{-}11)$$

$$U_{i\ ON}^{min} \leq U_{i\ \ ON} \leq U_{i\ ON}^{max} \qquad \forall i \qquad (6\text{-}12)$$

$$u_{s.char}(t) * P_{s.char}^{min}(t) \leq P_{s.char.grid}(t) \leq u_{s.char}(t) * P_{s.char}^{max}(t) \quad \forall s, \forall t \quad (6\text{-}13)$$

$$u_{s.dischar}(t) * P_{s.dischar}^{min}(t) \leq P_{s.dischar.app}(t)$$
$$\leq u_{s.dischar}(t) * P_{s.dischar}^{max}(t) \quad \forall s, \forall t \quad (6\text{-}14)$$

$$\mathrm{SOC}_s(t) = \mathrm{SOC}_s(t-1) + P_{s.char.grid}(t) - P_{s.dischar.app}(t) \quad \forall \mathrm{s}, \forall \mathrm{t} \quad (6\text{-}15)$$

$$\mathrm{SOC}_s(n\tau) = \mathrm{SOC}_s\big((n-1)\tau\big) + \sum_{t_{1=(n-1)\tau}}^{n\tau} (\ P_{s.char.grid}\ (t_1)$$
$$-P_{s.dischar.app}(t_1)\ ) \ \ \forall \mathrm{n}, \forall \mathrm{\tau}, \forall \mathrm{t_1} \in \{1, \dots, \mathrm{T}\}, \forall \mathrm{s} \qquad (6\text{-}16)$$

$$\mathrm{SOC}_s(t)^{min} \leq \mathrm{SOC}_s(t) \leq \mathrm{SOC}_s(t)^{max} \qquad \forall t \qquad (6\text{-}17)$$

$$u_i(t) \in [0,1] \qquad \forall \mathrm{i}, \forall \mathrm{t} \qquad (6\text{-}18)$$

$$u_{i.ini}(t=0) = \begin{cases} 0 & t_{ON.ini} \leq 0 \\ 1 & t_{ON.ini} > 0 \end{cases} \qquad \forall i, \forall t \qquad (6\text{-}19)$$

$$u_{i.ini}(t=\mathrm{n\tau}) = \begin{cases} 0 & t_{ON.ini.n\tau} \leq 0 \\ 1 & t_{ON.ini.n\tau} > 0 \end{cases} \quad \forall i, \forall t, \forall \tau, \forall n \qquad (6\text{-}20)$$

$$u_{s.char}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \qquad (6\text{-}21)$$

$$u_{s.dischar}(t) \in [0,1] \qquad \forall s, \forall t \tag{6-22}$$

$$u_{s.char}(t) + u_{s.dischar}(t) = 1 \qquad \forall s, \forall t \tag{6-23}$$

House B has 7 home appliances and 1 energy storage device. The scheduling of House B using the stochastic tool is subject to several constraints, including the household power constraints, the home appliances constraints, the storage devices constraints, and the rolling planning intertemporal constraints.

In the above constraints, the term τ in (6-2) refers to the length of time intervals covered in a single planning loop, which equals to m number of t. The total planning horizon T are divided into N number of time interval τ in (6-3). The scheduling results during each nth time interval τ are recorded.

The total power consumption (6-4) in the household considers the charging and discharging activities of energy storage s plus the power consumed by home appliances i. The household consumption is limited in (6-5), which cannot be exceeded throughout the rolling planning horizon T. The minimum operating time $T_{i.\ ON}$ is calculated in (6-6), it refers to the working time duration of an appliance once started. For example, process of washing machine cannot be interrupted. The maximum off time $T_{i.\ OFF}$ for each home appliances are limited in (6-8), which means during the maximal time period the home appliances can stay at the off status. Therefore, the home device should be switched on before its off time reaches its maximum value. In addition, it can be noted in (6-7) and (6-9) that the minimum operating time $T_{i.\ ON}$ and the maximum off time $T_{i.\ OFF}$ are associated with the appliances initial statuses $t_{ON.ini.n\tau}$, i.e. the time that the appliances have been on/off, at the beginning of each planning loop. Since the appliances cannot be all set back to a unified status at the beginning of every loop. Therefore, the statuses of the home appliances are updated at the start of each single planning loop. A sum of working time duration $U_{i\ ON.n\tau}$ of each appliances at every single planning loop is calculated in (6-10). This is also considered in the following planning loop so to make sure the total working time $U_{i\ ON}$ in (6-11) during the whole rolling planning horizon satisfies the boundaries of the total working time enforced in (6-12).

The State Of Charge (SOC) of the energy storage over the rolling planning horizon is computed in (6-15), it is associated with the charging $P_{s.char.grid}(t)$ and discharging power $P_{s.dischar.app}(t)$ at time t and the previous SOC state at time $t-1$. In a similar manner, the SOC of the battery at the start of each planning loop is calculated in (6-16). Since every kind of storage device has its own limitation on the energy capacity that can be stored in it, the maximum and minimum energy level of the storage is defined in (6-17). Furthermore, the energy storage charging and discharging power at every time slot is limited in (6-13) and (6-14).

Binary decision variables are defined in (6-18)–(6-23). The on and off status $u_i(t)$ of each home appliances at time t is indicated in (6-18). The updated initial statuses $u_{i.ini}(t = \mathrm{n}\tau)$ of home appliances are computed in (6-19) and (6-20) with updated $t_{ON.ini.n\tau}$ at time point nτ, which is the start of each planning loop. The decision variables of storage charging $u_{s.char}(t)$ and discharging $u_{s.dischar}(t)$ in (6-21) and (6-22) are used for implying when the storage charges or discharges. Equation (6-23) controls the energy storage devices can either charge or discharge, as both activities cannot happen at the same time.

6.3.2.2. House D

House D has seven home appliances, one energy storage and PV panels. The objective of scheduling House D is to minimize the bill payment. House D benefits from receiving FIT payments for the energy produced by the PV. Moreover, the energy storage and the PV are able to export energy back to the grid. By exporting energy, House D can earn exportation payments from FIT (it is assumed the energy storage receives the same ‘exportation’ tariff as in FIT). As a result, the bill payment considers the FIT payments in (6-24).

Objective function:

$$\underset{t}{Minimise}\, COST = \sum_{t=1}^{T} \left\{ \begin{matrix} P(t) * \pi(t) - P_{pv}(t) * \pi_{FIT.gen}(t) \\ -P_{pv.exp}(\mathrm{t}) * \pi_{FIT.exp}(t) - P_{s.\mathrm{exp}}(t) * \pi_{s.exp}(t) \end{matrix} \right\} \tag{6-24}$$

Subject to**:**

$$\tau = \mathrm{mt} \qquad \tau \in \{1, \dots, T\},\ t \in \{1, \dots T\},\ \forall\tau, \forall \mathrm{m}, \forall t \qquad (6\text{-}25)$$

$$\mathrm{N}\tau = T \qquad \forall\tau, \forall \mathrm{n} \in \{0, \dots, \mathrm{N}\} \qquad (6\text{-}26)$$

$$P(t) = \left\{\sum_{i=1}^{I} P_i u_i(t)\right\} + P_{s.char.grid}(t) - P_{s.dischar.app}(t) - P_{pv.ds}(\mathrm{t})$$

$$\forall i, \forall s, \forall pv, \forall t \qquad (6\text{-}27)$$

$$P_{min}(t) \le P(t) \le P_{max}(t) \qquad \forall t \qquad (6\text{-}28)$$

$$T_{i.\ ON} \ge \begin{cases} T_{i.\ op} \\ T_{i.\ op} - t_{ON.ini} & if\ u_{i.ini}(t=0) = 1 \end{cases} \qquad \forall i, \forall t \qquad (6\text{-}29)$$

$$T_{i.\ ON} \ge \begin{cases} T_{i.\ op} \\ T_{i.\ op} - t_{ON.ini.n\tau} & if\ u_{i.ini}(t=n\tau) = 1 \end{cases} \quad \forall i, \forall\tau, \forall t, \forall \mathrm{n} \qquad (6\text{-}30)$$

$$T_{i.\ OFF} \le \begin{cases} T_{i.\ off}^{max} \\ T_{i.\ off}^{max} + t_{ON.ini} & if\ u_{i.ini}(t=0) = 0 \end{cases} \qquad \forall i, \forall t \qquad (6\text{-}31)$$

$$T_{i.\ OFF} \le \begin{cases} T_{i.\ off}^{max} \\ T_{i.\ off}^{max} + t_{ON.ini.n\tau} & if\ u_{i.ini}(t=n\tau) = 0 \end{cases} \quad \forall i, \forall\tau, \forall t, \forall \mathrm{n} \qquad (6\text{-}32)$$

$$U_{i\ ON.n\tau} = 1^{\mathrm{n}\tau} * u_i(t) \qquad \forall \mathrm{n}, \forall\tau, \forall i, \forall t \qquad (6\text{-}33)$$

$$U_{i\ ON} = 1^T * u_i(t) \qquad \forall i, \forall t \qquad (6\text{-}34)$$

$$U_{i\ ON}^{min} \le U_{i\ ON} \le U_{i\ ON}^{max} \qquad \forall i \qquad (6\text{-}35)$$

$$u_{s.char}(t) * P_{s.char}^{min}(t) \le P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t)$$

$$\le u_{s.char}(t) * P_{s.char}^{max}(t) \qquad \forall s, \forall t \qquad (6\text{-}36)$$

$$u_{s.dischar}(t) * P_{s.dischar}^{min}(t) \le P_{s.dischar.app}(t) + P_{s.\mathrm{exp}}(t)$$

$$\leq u_{s.dischar}(t) * P_{s.dischar}^{max}(t) \quad \forall s, \forall t \qquad (6\text{-}37)$$

$$\mathrm{SOC}_s(t) = \mathrm{SOC}_s(t-1) + P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t)$$

$$-P_{s.dischar.app}(t) - P_{s.\exp}(t) \quad \forall \mathrm{s}, \forall \mathrm{t} \qquad (6\text{-}38)$$

$$\mathrm{SOC}_s(n\tau) = \mathrm{SOC}_s\big((n-1)\tau\big) + \textstyle\sum_{t_1=(n-1)\tau}^{n\tau}\big(P_{s.char.grid}(t_1) + P_{s.\mathrm{pv}char}(t_1) -$$

$$P_{s.dischar.app}(t_1) - P_{s.\exp}(t_1)\big) \quad \forall \mathrm{n}, \forall \tau, \forall \mathrm{t}_1 \in \{1, \dots, \mathrm{T}\}, \forall \mathrm{s} \quad (6\text{-}39)$$

$$\mathrm{SOC}_s(t)^{min} \leq \mathrm{SOC}_s(t) \leq \mathrm{SOC}_s(t)^{max} \qquad \forall t \qquad (6\text{-}40)$$

$$P_{pv}(\mathrm{t}) = P_{pv.ds}(\mathrm{t}) + P_{s.\mathrm{pv}char}(t) + P_{pv.exp}(\mathrm{t}) \qquad \forall pv, \forall s, \forall t \qquad (6\text{-}41)$$

$$P_{pv}^{min}(t) \leq P_{pv}(\mathrm{t}) \leq Percent.sun(t) * P_{pv}^{max}(t) \qquad \forall pv, \forall t \qquad (6\text{-}42)$$

$$P_{pv.ds}(\mathrm{t}) + P_{s.dischar.app}(t) \leq \textstyle\sum_{i=1}^{I} P_i u_i(t) \quad \forall i, \forall pv, \forall t \qquad (6\text{-}43)$$

$$u_i(t) \in [0,1] \qquad \forall \mathrm{i}, \forall \mathrm{t} \qquad (6\text{-}44)$$

$$u_{i.ini}(t=0) = \begin{cases} 0 & t_{ON.ini} \leq 0 \\ 1 & t_{ON.ini} > 0 \end{cases} \qquad \forall i, \forall t \qquad (6\text{-}45)$$

$$u_{i.ini}(t=\mathrm{n}\tau) = \begin{cases} 0 & t_{ON.ini.n\tau} \leq 0 \\ 1 & t_{ON.ini.n\tau} > 0 \end{cases} \quad \forall i, \forall t, \forall \tau, \forall n \qquad (6\text{-}46)$$

$$u_{s.char}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \qquad (6\text{-}47)$$

$$u_{s.dischar}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \qquad (6\text{-}48)$$

$$u_{s.char}(t) + u_{s.dischar}(t) = 1 \qquad \forall s, \forall t \qquad (6\text{-}49)$$

The rolling planning process has N number of planning loop with τ length of time, as defined in (6-25) and (6-26). The power consumption of House D in (6-27) considers the energy consumed by the devices and also the energy supplied by the energy storage $P_{s.dischar.app}(t)$ and PV productions $P_{pv.ds}(\mathrm{t})$. The limitation of the power consumption of House D is enforced in (6-28). The on and off statuses of home appliances are calculated in (6-29) and (6-31), which are also related to the initial statuses. At the beginning of each planning loop, the initial statuses are updated. Thus, the on and off statuses are recomputed in (6-30) and (6-32). The total running time of each home appliances during each planning loop is calculated in (6-33). Moreover, the total running time of each appliance across the whole planning horizon is calculated in (6-34) and limited in (6-35).

The energy storage can charge from the grid supply $P_{s.char.grid}(t)$ or/and the PV energy production $P_{s.\mathrm{pv}char}(t)$, as defined in (6-36). As presented in (6-37), it can discharge to supply the home appliances $P_{s.dischar.app}(t)$ or/and export back to the grid $P_{s.\exp}(t)$. The charging and discharging power limitations are also enforced in (6-36) and (6-37). The SOC of the energy storage is related to its charging and discharging activity. The SOC at each time is calculated in (6-38), and the SOC at the start of each planning loop is updated in (6-39). The capacity of the energy storage is reflected and limited in (6-40).

The PV production can supply the home appliances $P_{pv.ds}(\mathrm{t})$, charge the energy storage $P_{s.\mathrm{pv}char}(t)$ and export back to the grid $P_{pv.exp}(\mathrm{t})$, as indicated in (6-41). The energy produced by the PV $P_{pv}(\mathrm{t})$ is associated with the solar radiation $Percent.sun(t)$, therefore, the PV production is limited in (6-42). In addition, it is also limited in (6-43) that the energy supplied from the PV and the energy storage to the home appliances should not exceed their consumption at any time of the scheduling.

The binary variables in (6-45) are used to indicate the initial statuses of the home appliances at the beginning of the whole planning horizon. Furthermore, the initial statuses of the home appliances are updated at the beginning of each planning loop in (6-46). In order to decide when the home appliances will operate and when the energy storage will charge and discharge, binary variables in (6-44) and (6-47) - (6-49) are applied. In addition, it is limited in (6-49) that the charging and discharging activity of the energy storage cannot happen at the same time.

6.3.2.3. House G

House G has six home appliances, one storage heater, one energy storage, one EV and PV panels. The storage heater replaces one of the seven home appliances in House D. It needs to reach a pre-defined SOC level of heat stored before the customer returns to House G. Moreover, the energy stored in the EV battery needs to reach a target level set by the customer before it leaves the house in the morning. The EV will return to House G with a certain level of energy remaining in the battery. Thus, the EV will charge from the time it returns to the house until it leaves the next morning. In addition, the energy storage and the EV in House G can export energy to the grid to earn 'exportation' payments. The objective of House G is to minimise customer's bill payment as well.

Objective function:

$$\underset{t}{Minimise}\, COST = \sum_{t=1}^{T} \left\{ \begin{matrix} P(t) * \pi(t) - P_{pv}(t) * \pi_{FIT.gen}(t) \\ -P_{pv.exp}(\mathrm{t}) * \pi_{FIT.exp}(t) - P_{s.\mathrm{exp}}(t) * \pi_{s.exp}(t) \end{matrix} \right\}$$

(6-50)

Subject to**:**

$$\mathrm{\tau} = \mathrm{mt} \qquad \tau \in \{1, \dots, T\},\ t \in \{1, \dots T\},\ \forall \mathrm{\tau}, \forall \mathrm{m}, \forall t \qquad (6\text{-}51)$$

$$\mathrm{N}\tau = T \qquad \forall \mathrm{\tau}, \forall \mathrm{n} \in \{0, \dots, \mathrm{N}\} \qquad (6\text{-}52)$$

$$P(t) = \{\textstyle\sum_{i=1}^{I} P_i u_i(t)\} + P_{s.char.grid}(t) - P_{s.dischar.app}(t) - P_{pv.ds}(\mathrm{t}) +$$

$$P_{ev.char.grid}(t) + P_{sh.char.grid}(t) \qquad \forall i, \forall s, \forall pv, \forall ev, \forall sh, \forall t \in \{1, \dots, T\}$$

(6-53)

$$P_{min}(t) \le P(t) \le P_{max}(t) \qquad \forall t \qquad (6\text{-}54)$$

$$T_{i.\ ON} \ge \begin{cases} T_{i.\ op} & \\ T_{i.\ op} - t_{ON.ini} & if\ u_{i.ini}(t=0) = 1 \end{cases} \qquad \forall i, \forall t \qquad (6\text{-}55)$$

$$T_{i.\ ON} \geq \begin{cases} T_{i.\ op} \\ T_{i.\ op} - t_{ON.ini.n\tau} & if\ u_{i.ini}(t = n\tau) = 1 \end{cases} \quad \forall i, \forall \tau, \forall t, \forall \mathrm{n} \qquad (6\text{-}56)$$

$$T_{i.\ OFF} \leq \begin{cases} T_{i.\ off}^{max} \\ T_{i.\ off}^{max} + t_{ON.ini} & if\ u_{i.ini}(t = 0) = 0 \end{cases} \quad \forall i, \forall t \qquad (6\text{-}57)$$

$$T_{i.\ OFF} \leq \begin{cases} T_{i.\ off}^{max} \\ T_{i.\ off}^{max} + t_{ON.ini.n\tau} & if\ u_{i.ini}(t = n\tau) = 0 \end{cases} \quad \forall i, \forall \tau, \forall t, \forall \mathrm{n} \qquad (6\text{-}58)$$

$$U_{i\ ON} = 1^{T} * u_i(t) \qquad \forall i, \forall t \qquad (6\text{-}59)$$

$$U_{i\ ON.n\tau} = 1^{\mathrm{n\tau}} * u_i(t) \qquad \forall \mathrm{n}, \forall \tau, \forall i, \forall t \qquad (6\text{-}60)$$

$$U_{i\ ON}^{min} \leq U_{i\ ON} \leq U_{i\ ON}^{max} \qquad \forall i \qquad (6\text{-}61)$$

$$u_{s.char}(t) * P_{s.char}^{min}(t) \leq P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t) \leq u_{s.char}(t) * P_{s.char}^{max}(t) \quad \forall s, \forall t \qquad (6\text{-}62)$$

$$u_{s.dischar}(t) * P_{s.dischar}^{min}(t) \leq P_{s.dischar.app}(t) + P_{s.\exp}(t) + P_{s.dischar.ev}(t) + P_{s.dischar.sh}(t) \leq u_{s.dischar}(t) * P_{s.dischar}^{max}(t) \quad \forall s, \forall t \qquad (6\text{-}63)$$

$$\mathrm{SOC}_s(t) = SOC_s(t-1) + P_{s.char.grid}(t) + P_{s.\mathrm{pv}char}(t) - P_{s.dischar.app}(t) - P_{s.\exp}(t) - P_{s.dischar.ev}(t) - P_{s.dischar.sh}(t) \quad \forall \mathrm{s}, \forall \mathrm{t} \qquad (6\text{-}64)$$

$$\mathrm{SOC}_s(n\tau) = \mathrm{SOC}_s\big((n-1)\tau\big) + \sum_{t_{1=(n-1)\tau}}^{n\tau} \big(P_{s.char.grid}(t_1) + P_{s.\mathrm{pv}char}(t_1) - P_{s.dischar.app}(t_1) - P_{s.\exp}(t_1) - P_{s.dischar.ev}(t_1) - P_{s.dischar.sh}(t_1) \big) \quad \forall \mathrm{n}, \forall \tau, \forall \mathrm{t}_1 \in \{1, \ldots, \mathrm{T}\}, \forall \mathrm{s} \qquad (6\text{-}65)$$

$$SOC_s(t)^{min} \leq \mathrm{SOC}_s(t) \leq SOC_s(t)^{max} \qquad \forall \mathrm{s}, \forall t \qquad (6\text{-}66)$$

$$P_{pv}(\mathrm{t}) = P_{pv.ds}(\mathrm{t}) + P_{s.\mathrm{pv}char}(t) + P_{pv.exp}(\mathrm{t}) + P_{pv.ev}(\mathrm{t}) + P_{pv.sh}(\mathrm{t})$$

$$\forall pv, \forall s, \forall t \qquad (6\text{-}67)$$

$$P_{pv}^{min}(t) \leq P_{pv}(\mathrm{t}) \leq Percent.sun(t) * P_{pv}^{max}(t) \quad \forall pv, \forall t \qquad (6\text{-}68)$$

$$P_{pv.ds}(\mathrm{t}) + P_{s.dischar.app}(t) \leq \sum_{i=1}^{I} P_i u_i(t) \quad \forall i, \forall pv, \forall t \qquad (6\text{-}69)$$

$$u_{ev.char}(t_1) * P_{ev.char}^{min}(t) \leq P_{ev.char.grid}(t) + P_{s.dischar.ev}(t) + P_{pv.ev}(\mathrm{t})$$

$$\leq u_{ev.char}(t_1) * P_{ev.char}^{max}(t)$$

$$\forall s, \forall pv, \forall ev, \forall t_1 \in \{1, \dots, T\} (6\text{-}70)$$

$$\mathrm{SOC}_{ev}(t) = SOC_{ev}(t-1) + P_{ev.char.grid}(t) + P_{s.\mathrm{dischar}.ev}(t) + P_{pv.ev}(t)$$

$$\forall \mathrm{s}, \forall pv, \forall ev, \forall \mathrm{t} \qquad (6\text{-}71)$$

$$\mathrm{SOC}_{ev}(n\tau) = SOC_{ev}\big((n-1)\tau\big) + \sum_{t_1=(n-1)\tau}^{n\tau} (P_{ev.char.grid}(t_1) +$$

$$P_{s.\mathrm{dischar}.ev}(t_1) + P_{pv.ev}(t_1)) \qquad \forall \mathrm{n}, \forall \tau, \forall \mathrm{s}, \forall pv, \forall ev, \forall t_1 \in \{1, \dots, \mathrm{T}\} \qquad (6\text{-}72)$$

$$SOC_{ev}(t)^{min} \leq \mathrm{SOC}_{ev}(t) \leq SOC_{ev}(t)^{max} \qquad \forall \mathrm{ev}, \forall t \qquad (6\text{-}73)$$

$$\begin{cases} \mathrm{SOC}_{ev}\big(t_{ev.target} - n\tau\big) \geq \mathrm{SOC}_{ev.target} & if\ (t_{ev.target} - n\tau) > 0 \\ \mathrm{SOC}_{ev}\big(t_{ev.target} - n\tau + T\big) \geq \mathrm{SOC}_{ev.target} & if\ (t_{ev.target} - n\tau) \leq 0 \end{cases}$$

$$\forall \mathrm{n}, \forall \tau, \forall \mathrm{ev}, \forall t_{ev.target} \in \{1, \dots, T\} \quad (6\text{-}74)$$

$$u_{sh.char}(t) * P_{sh.char}^{min}(t) \leq P_{sh.char.grid}(t) + P_{s.dischar.sh}(t) + P_{pv.sh}(\mathrm{t})$$

$$\leq u_{sh.char}(t) * P_{sh.char}^{max}(t)$$

$$\forall s, \forall pv, \forall sh, \forall t \qquad (6\text{-}75)$$

$$\mathrm{SOC}_{sh}(t) = SOC_{sh}(t-1) + P_{sh.char.grid}(t) + P_{s.\mathrm{dischar}.sh}(t) + P_{pv.sh}(t) -$$

$$P_{sh.\mathrm{dischar}}(t) \qquad \forall \mathrm{s}, \forall pv, \forall sh, \forall \mathrm{t} \qquad (6\text{-}76)$$

$$\mathrm{SOC}_{sh}(n\tau) = SOC_{sh}(n\tau - 1) + \sum_{t_1=(n-1)\tau}^{n\tau} \left(P_{sh.char.grid}(t_1) + P_{s.\mathrm{dischar}.sh}(t_1) + P_{pv.sh}(t_1) - P_{sh.\mathrm{dischar}}(t_1) \right) \ \forall \mathrm{n}, \forall \tau, \forall \mathrm{s}, \forall pv, \forall sh, \forall \mathrm{t}_1 \in \{1, \dots, \mathrm{T}\} \tag{6-77}$$

$$SOC_{sh}(t)^{min} \leq \mathrm{SOC}_{sh}(t) \leq SOC_{sh}(t)^{max} \qquad \forall \mathrm{sh}, \forall t \tag{6-78}$$

$$\begin{cases} \mathrm{SOC}_{sh}(t_{sh.target} - n\tau) \geq \mathrm{SOC}_{sh.target} & if\ (t_{sh.target} - n\tau) > 0 \\ \mathrm{SOC}_{sh}(t_{sh.target} - n\tau + T) \geq \mathrm{SOC}_{sh.target} & if\ (t_{sh.target} - n\tau) \leq 0 \end{cases}$$

$$\forall \mathrm{n}, \forall \tau, \forall \mathrm{sh}, \forall t_{sh.target} \in \{1, \dots, T\} \tag{6-79}$$

$$u_i(t) \in [0,1] \qquad \forall \mathrm{i}, \forall \mathrm{t} \tag{6-80}$$

$$u_{i.ini}(t = 0) = \begin{cases} 0 & t_{ON.ini} \leq 0 \\ 1 & t_{ON.ini} > 0 \end{cases} \qquad \forall i, \forall t \tag{6-81}$$

$$u_{i.ini}(t = \mathrm{n}\tau) = \begin{cases} 0 & t_{ON.ini.n\tau} \leq 0 \\ 1 & t_{ON.ini.n\tau} > 0 \end{cases} \quad \forall i, \forall t, \forall \tau, \forall n \tag{6-82}$$

$$u_{s.char}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \tag{6-83}$$

$$u_{s.dischar}(t) \in [0,1] \qquad \forall \mathrm{s}, \forall \mathrm{t} \tag{6-84}$$

$$u_{s.char}(t) + u_{s.dischar}(t) = 1 \qquad \forall s, \forall t \tag{6-85}$$

$$u_{ev.char}(t_1) \begin{cases} \in [0,1] & \forall t_1 \in t_{ev.char} \\ = 0 & \forall t_1 \notin t_{ev.char} \end{cases}$$

$$\forall t_{ev.char} \in \begin{cases} \{1, \dots, t_{ev.target} - \mathrm{n}\tau, t_{ev.return} - \mathrm{n}\tau, \dots, T\} & if\ (t_{ev.target} - \mathrm{n}\tau) > 0 \\ \{t_{ev.return} - \mathrm{n}\tau, \dots, \mathrm{T} + (t_{ev.target} - \mathrm{n}\tau)\} & if\ t_{ev.target} - \mathrm{n}\tau \leq 0 \text{ and } t_{ev.return} - \mathrm{n}\tau > 0 \\ \{1, \dots, T + (t_{ev.target} - \mathrm{n}\tau), T + (t_{ev.return} - \mathrm{n}\tau), \dots, \mathrm{T}\} & if (t_{ev.return} - \mathrm{n}\tau) \leq 0 \end{cases} \tag{6-86}$$

$$u_{sh.char}(t) \in [0,1] \qquad \forall \mathrm{sh}, \forall \mathrm{t} \tag{6-87}$$

The rolling planning procedure divides the whole scheduling horizon to N number of planning loops with τ length of time, which are defined in (6-51) and (6-52). The total power consumption of House G in (6-53) considers the consumption of the home appliances, the charging and discharging activities of the energy storage, the energy supplied by the PV, and the charging activities of the EV $P_{ev.char.grid}(t)$ and the storage heater $P_{sh.char.grid}(t)$. Moreover, the total power consumption is limited in (6-54). The on and off statuses of the home appliances are decided based on the minimum running time (6-55), the maximum off time (6-57) and the total running time (6-59). The minimum running time and the maximum off time are associated with the initial statuses of the home appliances, which is calculated in (6-81). In addition, the initial statuses of the appliances are updated at the beginning of every planning loop in (6-82). Based on the updated initial statuses, the minimum running time and the maximum off time are also recomputed in (6-56) and (6-58). The total running time of the home appliances is also refreshed at the start of each loop in (6-60). Limitation of the total running time across the whole scheduling horizon is enforced in (6-61).

The energy storage can charge from the grid supply and the PV production in (6-62). It can discharge to supply the appliances, the EV, the storage heater, and it can also export its stored energy to the grid in (6-63). Moreover, the charging and discharging power are limited in (6-62) and (6-63) as well. The SOC level stored in the energy storage is related to its charging and discharging activities, as defined in (6-64). At the beginning of each planning loop, the SOC level is also updated based on (6-65). The storage capacity is limited in (6-66).

The PV can supply the devices (home appliances, EV $P_{pv.ev}(\mathrm{t})$ and storage heater $P_{pv.sh}(\mathrm{t})$), charge the energy storage, and export to the grid, as defined in (6-67). The PV production capacity is indicated in (6-68). It is also limited in (6-69) that the energy supplied from the PV and the energy storage to the home appliances should not exceed the energy consumed by themselves.

The EV can charge from the grid supply $P_{ev.char.grid}(t)$, the energy storage $P_{s.dischar.ev}(t)$, the PV $P_{pv.ev}(\mathrm{t})$, as presented in (6-70). It charges when it is connected to House G, as defined in (6-86). The SOC level of the EV battery $\mathrm{SOC}_{ev}(t)$ therefore relates to the charging activity, which is defined in (6-71). The SOC level of the EV is updated at the start of each loop in (6-72). At time $t_{ev.target}$, the EV needs to reach its target SOC level $\mathrm{SOC}_{ev.target}$ before it leaves the house. Considering the rolling optimisation, the target time also rolls forward with the process in (6-74). The capacity of the EV battery is limited in (6-73).

Similar to the EV, the storage heater can charge from the grid supply $P_{sh.char.grid}(t)$, the energy storage $P_{s.dischar.sh}(t)$ and PV production $P_{pv.sh}(\mathrm{t})$ in (6-75). As long as there is heat stored in the energy storage, it has a discharging (heat dispensing) rate $P_{s.\mathrm{dis}char.sh}(t)$. Therefore, the SOC level of the storage heater $\mathrm{SOC}_{sh}(t)$ is associated with the charging and discharging activities of the storage heater, as calculated in (6-76). Furthermore, the heat energy stored in the storage heater is updated at the beginning of every planning loop in (6-77). The SOC level of the storage heater need to reach a pre-defined target level $\mathrm{SOC}_{sh.target}$ at time $t_{sh.target}$, and the target time rolls forward in (6-79) with the rolling planning process. The capacity of the storage heater is enforced in (6-78).

Binary variables in (6-80), (6-83) - (6-85), (6-86) and (6-87) determine when the home appliances will operate, when the storage will charge and discharge, and when the EV and the storage heater will charge, respectively. It is limited in (6-85) that the charging and discharging activity of the energy storage cannot occur at the same time.

Results of case studies of the stochastic tool are presented in the following section, together with a detailed illustration of the application of the rolling planning and scenario tree in the stochastic tool.

6.3.3. Case Studies of Stochastic Scheduling Tool

This section will first illustrate the detailed steps of how the stochastic scheduling tool schedule the home appliances by combining the rolling planning and RTP scenario trees. The steps and flow chart described in the following section can be used as a general approach of employing the stochastic scheduling tool with different time interval configurations.

Case studies are carried out in House B, House D and House G. The results are shown in section 6.3.3.2. Different cases of external notification are used to present the capability of the stochastic tool in the three houses.

6.3.3.1. Case Study Steps

The rolling planning process illustrated in the case studies covers 24 hours for the next day. The time interval configured in the planning procedure is 3 hours, so there will be 8 planning loops. Detailed steps of the stochastic scheduling tool application are presented as a flow chart in Figure 6-3.

Before starting the whole rolling planning procedure, an ARIMA time series model is fitted and evaluated to the historical RTP price data. The PJM energy RTP data [105] is used as the past dataset, and an ARMA(4, 4) forecast model is built through a number of procedures which are introduced in detail in Chapter 4.

At the beginning of the whole procedure, the planning time counter is initialized to zero. A two-stage RTP scenario tree, as illustrated in Figure 6-2, for the first planning loop is constructed at this point by applying scenario generation and scenario reduction Steps. One thousand scenarios for the future 24 hours are generated by means of sampling the error term distribution in the ARMA (4, 4) time series model, which follows Gaussian distribution with zero mean value and a constant variance. Five out of one thousand generated scenarios are selected through the forward selection algorithm based on probability distances, and the five selected scenarios are applied as the paths between the first-stage node and second-stage nodes represent the corresponding optimal scheduling solutions in the two-stage RTP scenario tree in Figure 6-2.

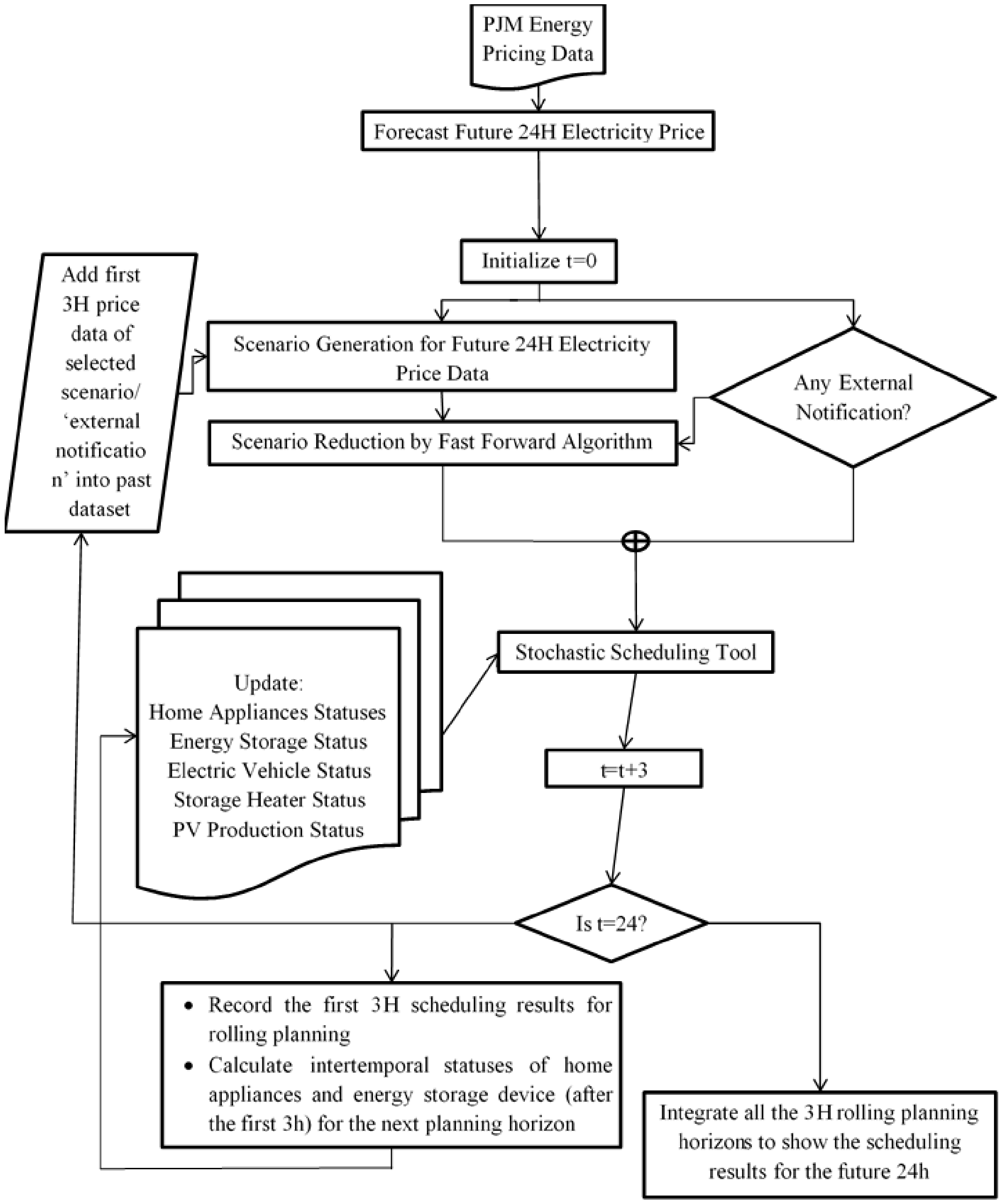


Figure 6-3 Case Study Flow Chart of Stochastic Customer-centred Scheduling Tool

All the five selected potential scenarios in the tree are input into the stochastic scheduling tool, and the scheduling results are stored to be used in the next planning loop. The scheduling results of the five potential scenarios are represented by the second-stage nodes in the two-stage RTP scenario tree in Figure 6-2. The realization of the planning decision at each time interval is made at the beginning of every single planning loop. At the start of each planning loop, the system checks if there is any external notifications/signals sent from operators/aggregators. If there are external notifications, the decision will be revised according to the external signals. If not, the RTP scenario with the highest probability of occurrence and the corresponding scheduling results will be selected.

The stochastic scheduling tool reschedules the load appliances when one planning loop executes. It schedules the load devices for the future 24 hours, although only the first three hours scheduling results are recorded and used. The reason for scheduling and forecasting for the next 24 hours is to achieve optimal redistributed results for home appliances, by considering the future trend of energy price rates. In addition, the 24-hour scheduling at each planning stage performs as a back-up solution. The time counter is updated by adding three hours when the scheduling of one loop is completed.

After the planning in one time interval is complete, the first 3-hours dynamic pricing rates of the selected scenario or the external notifications signal are added into the past data. New RTP scenario trees are constructed at the beginning of each planning loop based on the updated historical data. In the meantime, the first 3-hours scheduling results are recorded and applied as well. Intertemporal statuses of the home appliances, the storage device, the EV, the storage heater and the PV production are calculated to be used at the beginning of the next planning loop.

The iterative process will not terminate until the rolling planning time counter reaches the value of 24, which means the stochastic scheduling tool has planned for the next day. Note that the rolling planning procedure proposed here is not limited to a time period of 24 hours. It can be used for a continuing basis for long-term planning in a recurring and repetitive manner, as every single planning loop covers 24 hours in the near future.

The stochastic scheduling tool opens to external notifications/price signals sent from network operators/ aggregators, so it allows the possibility to revise the real-time energy price input signal. Therefore, it can provide flexibility coming from active demand side participation to accommodate the stochastic factors happening in the grid.

6.3.3.2. Case Study Results

The case study configurations applied in the stochastic scheduling tool is the same as stated in Section 3.2.4.1 in Chapter 3. For the houses that are able to export the energy from the PV and the energy storage device to the grid, the 'exportation' tariff is assumed to be 90% of the energy prices applied to the house. By assuming this, it will ensure the house is scheduled to meet its own consumption first, and then also export a certain amount of energy to earn 'exportation' payment. All the parameters values in the constraints are decided and changeable by consumers themselves and configured as input into the tool. This means consumers have chances to modify their energy usage preferences.

In the case studies, the time interval of the planning is three hours, which means eight planning loops are processed during the 24 hours. At the start of each planning loop, the tool opens to external notifications to see if there is any notification of price alteration imposed by aggregators/ network operator. House B, House D and House G are used for case studies, with two different scenarios of external notification of price change during the rolling planning procedure tested in the stochastic tool. Scenario 1 alters the forecasted price in one planning loop to lower values, according to an assumed external notification. In addition to the change made in the first scenario, scenario 2 changes the forecasted price in another planning loop to higher values. The PJM RTP energy price data [105] is used to simulate the application of rolling planning by assuming perfect information are available during the case study. Case study results are presented in the following sections.

6.3.3.2.1. Scenario 1

In scenario 1, during the rolling planning process, for the first three hours of the scheduling, it is informed by the external notification that the price will be lower than the forecasted price. The prices used in the stochastic tool (i.e. the rolling planning process) under scenario 1 are illustrated as the grey line of the upper curve in Figure 6-2. The forecasted prices, which record the first three hours prices of the 8 planning loops, are shown as the light blue dash line of the upper curve in Figure 6-2. For the first three hours, i.e. from 1 am to 3 am, the forecasted price rates (dashed blue curve) at the first planning loop in Figure 6-2 was supposed to be selected, as it has the highest probability of occurrence. By comparing the forecasted prices and the final prices used in the rolling planning process, it can be observed that the prices of the first three hours are altered to be lower, due to external notification of change. Case study results of House B, House D and House G scheduled by the stochastic tool under scenario 1 are illustrated in the sections below.

6.3.3.2.1.1. Case Study Results of House B – Scenario 1

The scheduling results of House B is presented at the bottom part of Figure 6-4. The stochastic tool schedules the home appliances to run at lower price periods (1-3 a.m. and 2- 7 p.m.). The cooking devices are scheduled to operate at 5-6 p.m. when customers return to the house. This also applies to the TV, which is scheduled to run at 6 p.m.

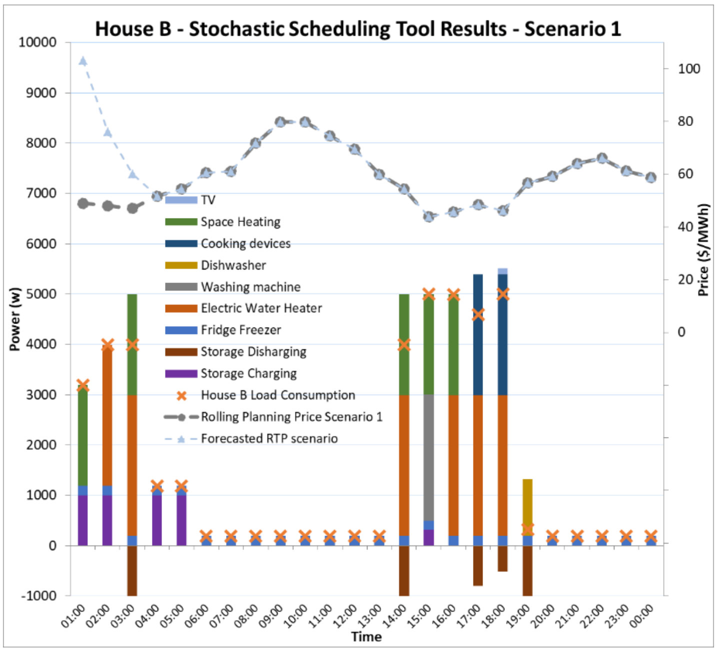


Figure 6-4 Case Study Results of the Stochastic Scheduling Tool in House B under Scenario 1

The energy storage also charges during the lower price periods. The charging and discharging activities of the energy storage can be found in Figure 6-5. It charges at 1= 2 a.m. and 4-5 a.m. at its maximum power. Then it charges 310W at 3 p.m. without breaching the total energy consumption limitation of 5kW. It discharges at 3 a.m., 2 p.m. and 5-7 p.m. to lower the consumption from the grid supply and to ensure the total consumption does not exceed the 5kW limit.

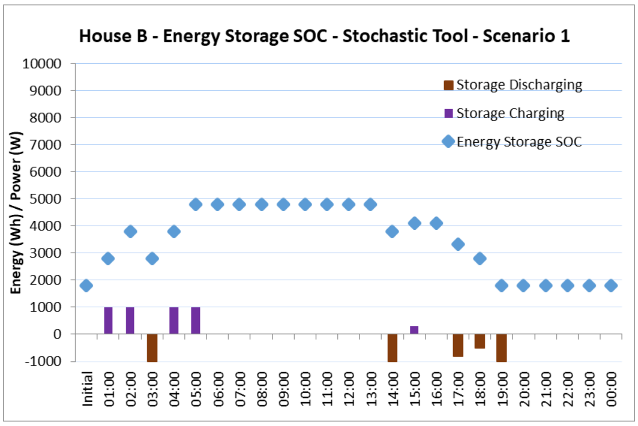


Figure 6-5 Energy Storage Charging and Discharging Activities and Its SOC Scheduled by the Stochastic Tool in House B under Scenario 1

6.3.3.2.1.2. Case Study Results of House D – Scenario 1

Scheduling results of home appliances and its energy supplies are given in Figure 6-6. Similar to House B, the stochastic tool schedules the appliances towards lower price periods under scenario 1. With the additional PV production, the household consumption is lowered, especially during the time from 2 p.m. to 6 p.m. PV production is presented in Figure 6-7. It can be observed that the majority of the PV production is exported to the grid when the energy prices are higher from 7 a.m. to 1 p.m., in order to earn higher exportation payment. Moreover, at 7 p.m., the PV exported a small amount of energy (20W) after satisfying the household consumption. In addition to the PV energy exportation, the energy storage also discharges energy to the grid between 8 and11 a.m. The charging and discharging activities of the energy storage are illustrated in Figure 6-8. It can be noticed that, at 8 a.m. and 10 p.m., the energy storage first supplies the household consumption, then discharges to the grid, as there is a 1kW/h maximum discharging rate limitation. It charges at lower price periods (1 a.m., 4–5 a.m., 4 and 6 p.m.) and discharges at times when prices are higher.

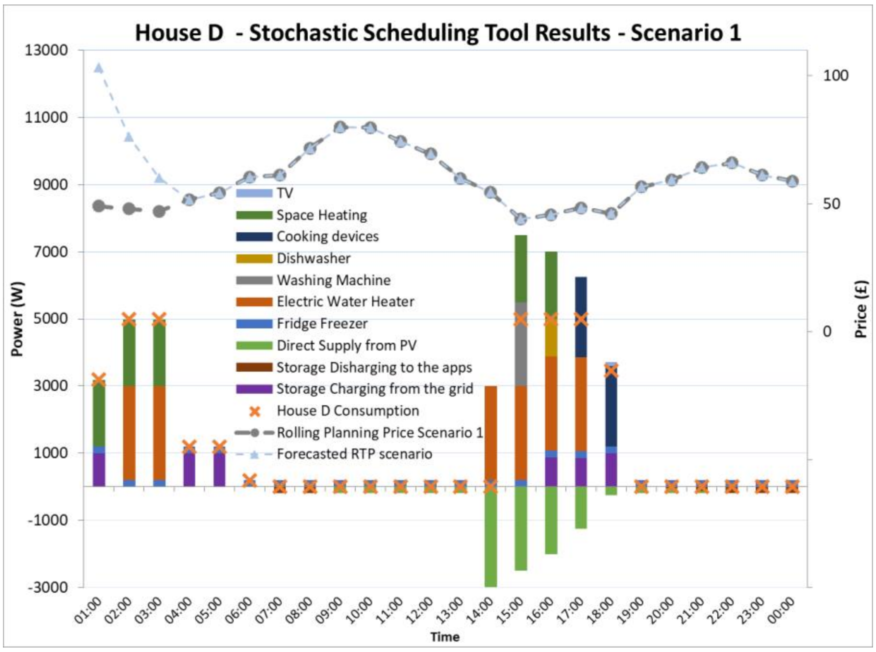


Figure 6-6 Case Study Results of the Stochastic Scheduling Tool in House D under Scenario 1

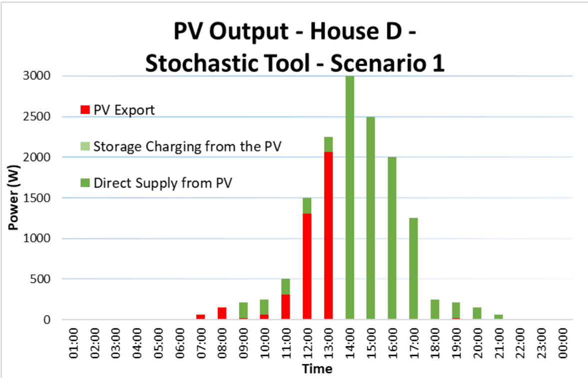


Figure 6-7 PV Scheduled by the Stochastic Tool in House D under Scenario 1

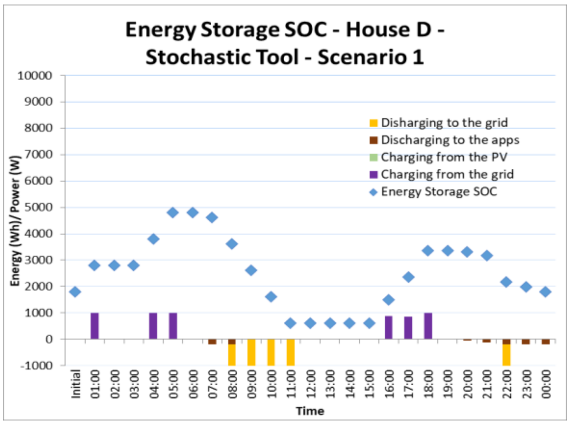


Figure 6-8 Energy Storage Charging and Discharging Activity and Its SOC Scheduled by the Stochastic Tool in House D under Scenario 1

6.3.3.2.1.3. Case Study Results of House G - Scenario 1

Comparing to House D, House G has an additional EV, which has a maximum charging power of 5kW/h. It also replaces the space heating with a storage heater. Therefore, the maximum power allowance in House G is 10kW at any time of the scheduling. PV and energy storage are able to export energy to earn 'exportation' payments.

The scheduling results of House G under scenario 1 are presented in Figure 6-9. It shows that the home appliances and the charging activities of the energy storage, the storage heater and the EV are scheduled when energy prices are lower in scenario 1 (1-5 a.m. and 3-7 p.m.). The larger consumption appliances run at 2-3 a.m. and 3-6 p.m. when the prices are the lowest.

The storage heater charges from the grid supply at 1-5 a.m. and 6 p.m. Detailed charging activities of the storage heater can be found in Figure 6-10. The energy storage supplies the storage heater at 6 a.m. Moreover, the PV supplies the storage heater from 12 to 5 p.m., when the PV production is high. The PV production is given in Figure 6-11. From 9 a.m. to 2 p.m., when the energy prices are higher, the PV exports its energy to the grid. In addition, at 1 p.m. and 3-4 p.m., the PV charges the energy storage after satisfying the energy consumption of the home appliances and the storage heater. At 7 p.m., the PV supplies a small amount (20W) of its energy to the EV.

The EV charging activities are presented in Figure 6-12. In the morning, the EV charges at its maximum rate (5kW/h) at 2 and 3 a.m., when the prices are the lowest during the period before it leaves the house at 7 a.m. The EV returns to House G at 6 p.m. and starts its charging activity from 7 p.m. However, from 7 p.m., the energy prices are starting to be higher. Thus, the energy storage supplies the EV charging at its maximum discharging power (1kW/h) at 7 p.m. and 0 a.m. Furthermore, as mentioned above, the PV also supplies a small amount of energy to the EV at 7 p.m.

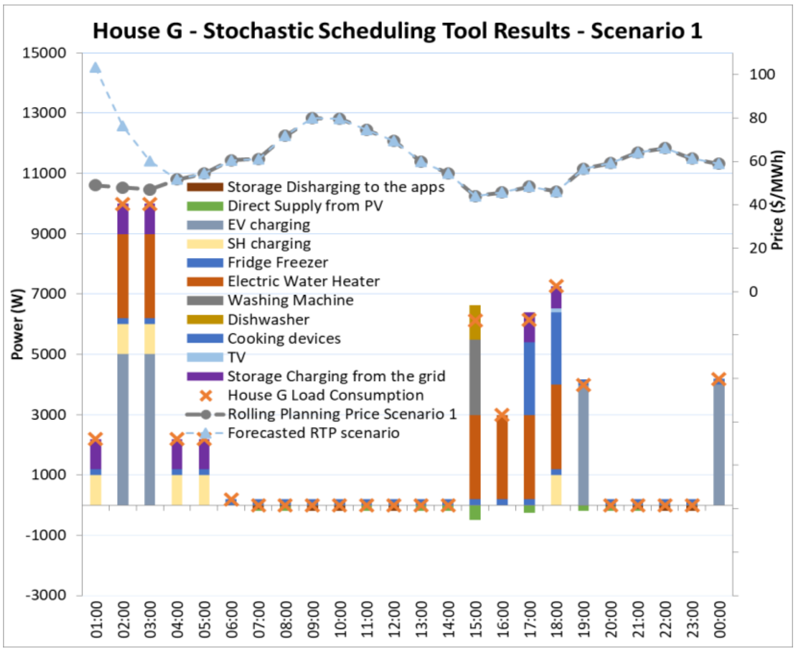


Figure 6-9 Case Study Results of the Stochastic Scheduling Tool in House G under Scenario 1

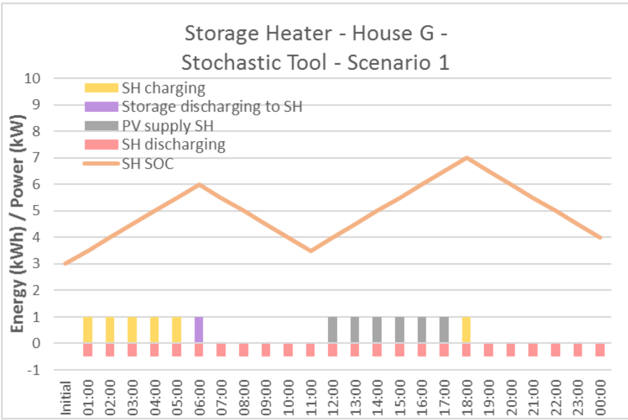


Figure 6-10 Storage Heater Activity and Its SOC Scheduled by the Stochastic Tool in House G under Scenario 1

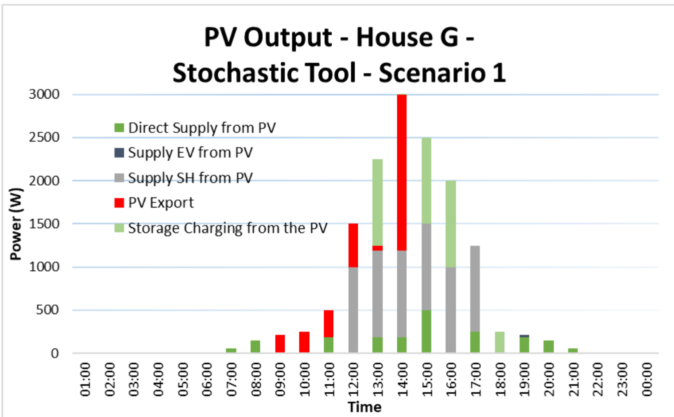


Figure 6-11 PV Scheduled by the Stochastic Tool in House G under Scenario 1

Detailed charging and discharging activities of the energy storage are illustrated in Figure 6-13. The energy storage charges from the grid supply for the first 5 hours of the scheduling. It then discharges to heat the storage heater at 6 a.m. From 7 a.m. to 12 p.m., the energy storage discharges to supply the house consumption and exports energy to the grid. This is because the energy prices during the period are high. It charges from the PV and the grid supply between 1 and 6 p.m., when the PV production is high and when the energy price (at 5 and 6 p.m.) is low. Besides discharging its energy to charge the EV at 7 p.m. and 0 a.m., the energy storage discharges to supply the home appliances and exports to the grid between 9 and 11 p.m. The SOC level at the end of the scheduling stays the same as that at the start.

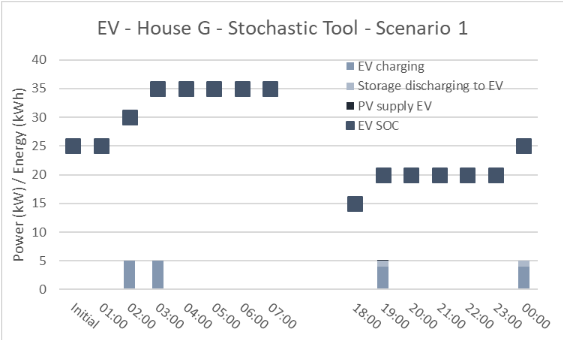


Figure 6-12 EV Activity and Its SOC Scheduled by the Stochastic Tool in House G under Scenario 1

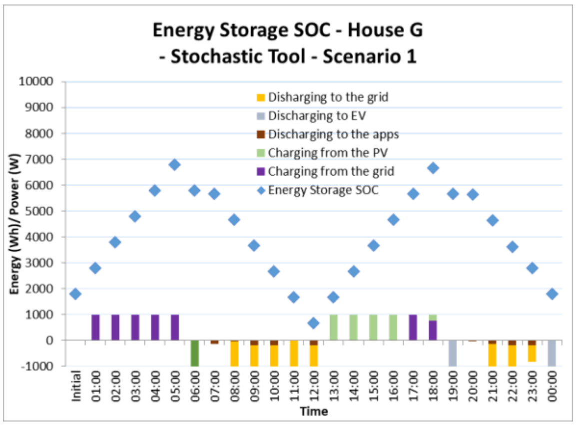


Figure 6-13 Energy Storage Charging and Discharging Activities and Its SOC Scheduled by the Stochastic Tool in House G under Scenario 1

6.3.3.2.2. Scenario 2

The rolling planning RTP scenario 2 together with the forecasted RTP rates are illustrated on the top of Figure 6-14. It can be observed that the forecasted prices (dashed blue curve) under Scenario 2 are modified in two planning loops by the external information, rather than selecting scenarios with the highest probability of occurrence from the constructed forecasting scenario trees. The external notification suggests the price rates are lower in the first three hours. Furthermore, unexpected sharp peak price rates occurred during the morning time (7- 9 a.m.). As a result of that, the forecasted price rates are changed to higher energy pricing values. It can be noted that due to the unexpected peak price, the energy prices after 9 a.m. in scenario 2 are different from that in scenario 1. This is because the prices are forecasted based on the historical data. If the prices in one planning loop change, the price rates will change in the following planning loops. House B, House D and House G are used for case studies of the stochastic tool under scenario 2.

6.3.3.2.2.1. Case Study Results of House B – Scenario 2

The case study scheduling results of House B scheduled by the stochastic scheduling tool under scenario 2 are presented in Figure 6-14. It can be discovered from Figure 6-14 that House B is scheduled to have higher consumption during lower electricity price time (1- 4 a.m. and 3- 8 p.m.). The energy storage discharges between 4- 7 p.m. to ensure the household consumption does not exceed the consumption allowance of 5kW. The charging and discharging activities of the energy storage can be found in Figure 6-15. The energy storage charges at the first 2 hours of the scheduling, then it discharges to lower the consumption at 3 a.m. After that, it charges at 4 a.m. and 2 p.m., in order to discharge between 4 and 8 p.m. Although the space heating is scheduled to run at 8 p.m. when the prices are a bit higher, the energy storage discharges at that time to lower the consumption.

2.1.1.1.1.1. Case Study Results of House D – Scenario 2

The scheduling results of House D using the stochastic scheduling tool under scenario 2 is presented in Figure 6-16. The price scenario 2 has lower prices at 1-6 am and 3 - 7 pm. During these time periods, home appliances are scheduled to operate. Moreover, the energy storage also charges during these time periods, as indicated in Figure 6-17. The energy storage discharges at the first hour of the scheduling. Then it charges from 2 to 6 a.m. to take advantage of the lower price period. Between 7 and 10 a.m., the energy storage exports its energy when the prices are high. At 12 p.m., the energy storage discharges to supply the water heater. From 1 to 5 p.m., it charges from the PV energy and the grid supply. Later in the day, from 9 p.m., the energy storage discharges to supply the home appliances and exports its majority of energy to the grid. The SOC level stored in the energy storage at the end of the schedule remains the same as that at the start.

The PV production of House D under scenario 2 is presented in Figure 6-18. The PV supplies its majority of production to lower household consumption.

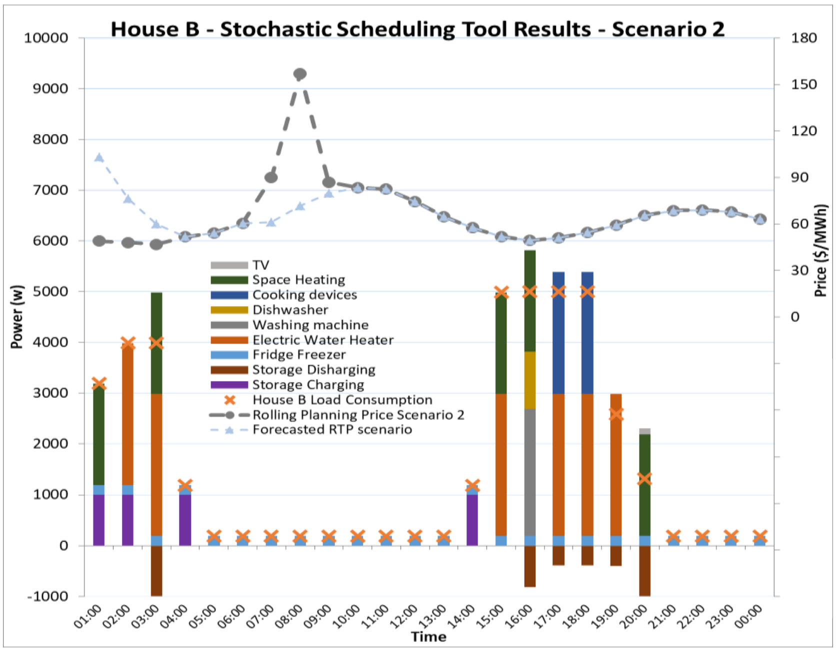


Figure 6-14 Case Study Results of the Stochastic Scheduling Tool in House B under Scenario 2

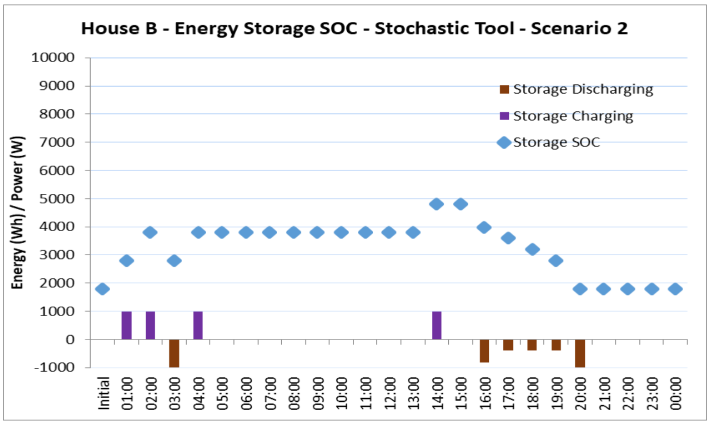


Figure 6-15 Energy Storage Charging and Discharging Activities and Its SOC Scheduled by the Stochastic Tool in House B under Scenario 2

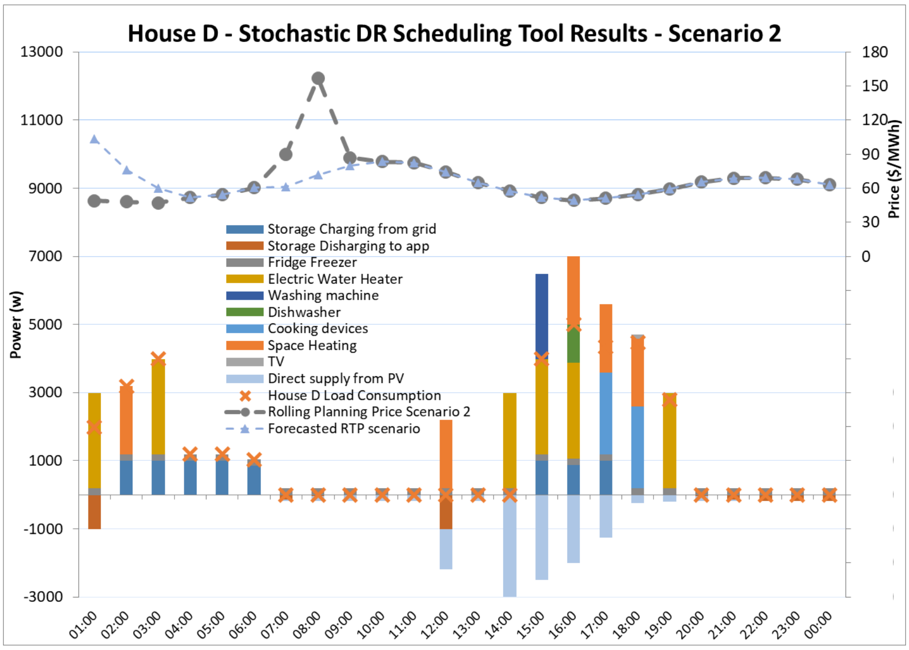


Figure 6-16 Case Study Results of the Stochastic Scheduling Tool in House D under Scenario 2

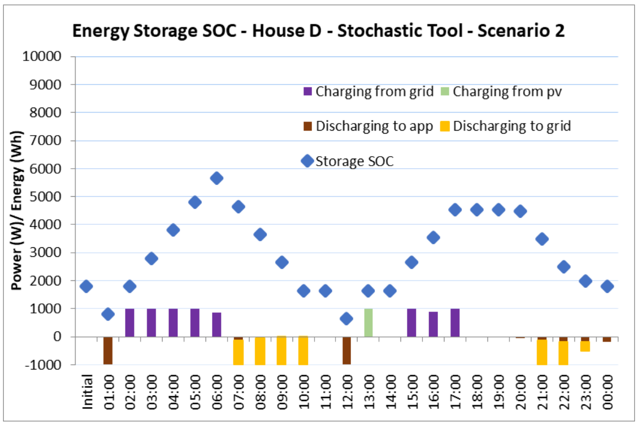


Figure 6-17 Energy Storage Charging and Discharging Activities and Its SOC Scheduled by the Stochastic Tool in House D under Scenario 2

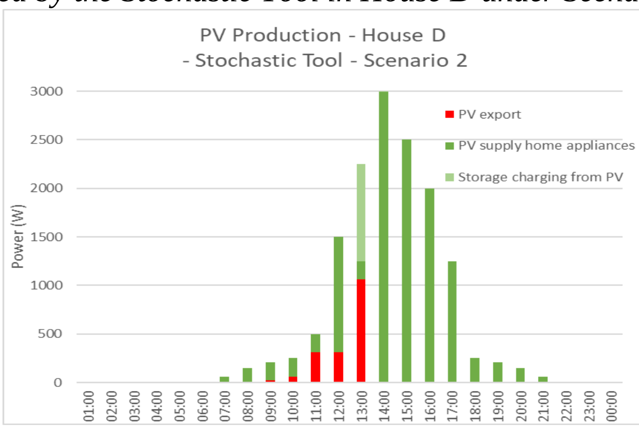


Figure 6-18 PV Scheduled by the Stochastic Tool in House D under Scenario 2

Between 9 a.m. to 1 p.m., the PV exports its energy after satisfying the energy consumption in House D, when the energy prices are high, i.e. high ‘exportation’ rates that is equal to 90% of the dynamic price rates.

2.1.1.1.1.2. Case Study Results of House G – Scenario 2

As illustrated in Figure 6-19, the stochastic scheduling tool schedules House G to consume more power during the low electricity price period (at 1-5 a.m. and 3-7 p.m.). Comparing to House B and House D, the consumption of House G is apparently larger due to more devices are connected in the house.

The energy storage charges from the grid supply from 1 to 5 a.m. in Figure 6-20. It discharges to heat the storage heater at 6 and 11 a.m. Between 7 and 12 a.m., the energy storage discharges to supply the household consumption, and exports the surplus energy to the grid. At 2 and 3 p.m., the energy storage charges from the PV production. Then it charges from the grid supply for the following three hours. At 7 p.m. and 0 a.m., the energy storage discharges to supply the EV charging. From 8 p.m. until the end of the day, the energy storage supplies the household consumption. Moreover, it exports to the grid at 10 p.m. The SOC level of the energy storage at the end of the day is the same as that of when the schedule begins.

During the low price period (1-4 a.m. and 5-6 p.m.), the storage heater charges from the grid supply, as presented in Figure 6-21. At 6 a.m., the storage heater charges from the energy storage. From 11 a.m. to 4 p.m., the majority of the energy that charges the storage heater comes from the PV production, when the PV production is high.

The PV production is given in Figure 6-22. During 9 a.m.-2 p.m. and 7-9 p.m., part of the PV energy is exported to the grid to earn FIT payments, which is represented by red bars in the figure. The remaining PV production supplies the home devices, charges the energy storage and the storage heater. There is no PV supply to the EV charging, as no/very low PV production is available when the EV charges at 2-3 a.m., 7 p.m. and 0 a.m.

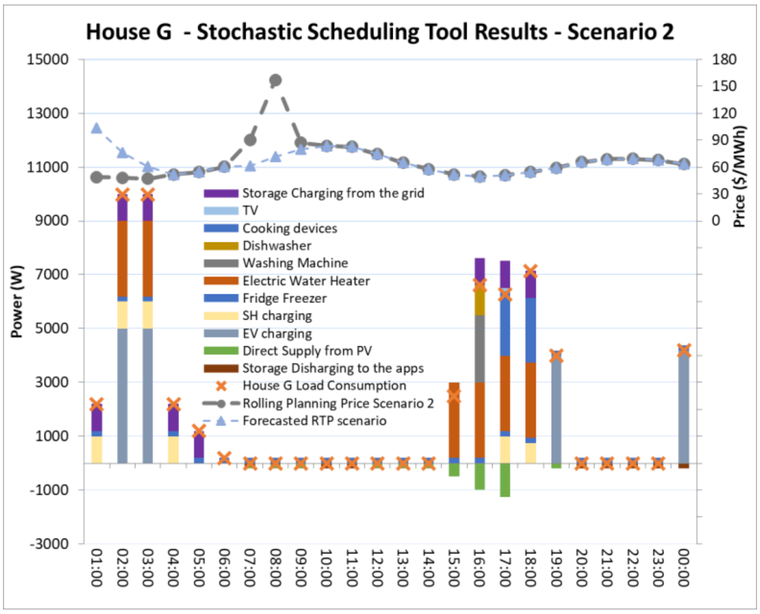


Figure 6-19 Case Study Results of the Stochastic Scheduling Tool in House G under Scenario 2

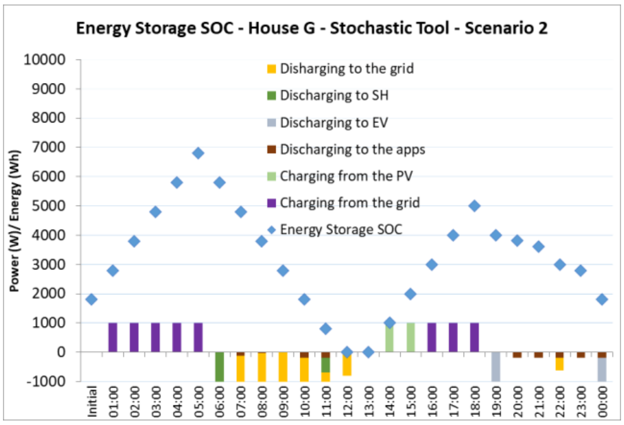


Figure 6-20 Energy Storage Charging and Discharging Activities and Its SOC Scheduled by the Stochastic Tool in House G under Scenario 2

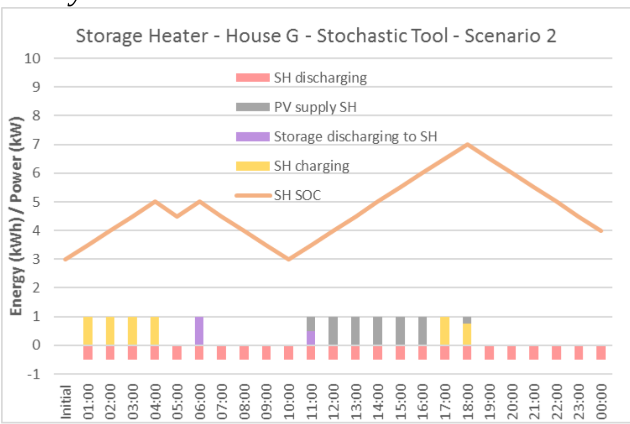


Figure 6-21 Storage Heater Activity and Its SOC Scheduled by the Stochastic Tool in House G under Scenario 2

The EV charge at 2 and 3 a.m. before it leaves the house, as presented in Figure 6-23. It returns home at 6 p.m. with 15kWh energy left in the battery. It charges from the grid supply and the energy storage at 7 p.m. and 0 a.m. The energy storage discharges at its maximum rate to supply the EV during these two time slots.

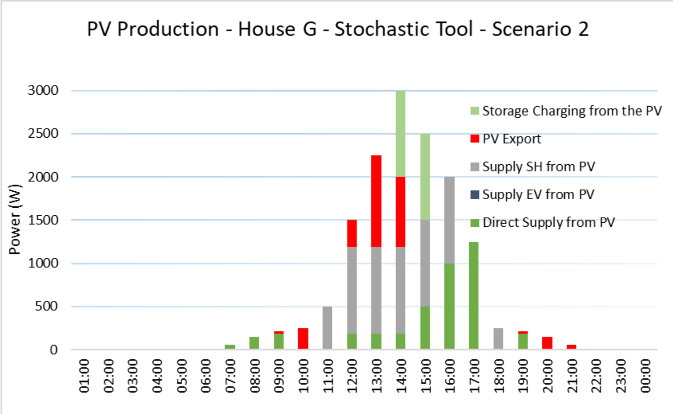


Figure 6-22 PV Scheduled by the Stochastic Tool in House G under Scenario 2

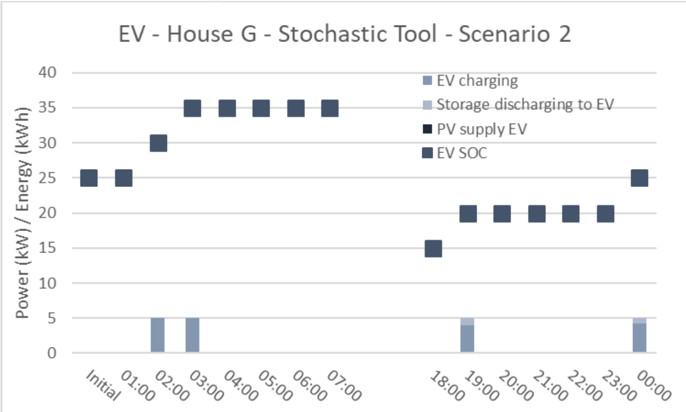


Figure 6-23 EV Activity and Its SOC Scheduled by the Stochastic Tool in House G under Scenario 2

6.3.4. Discussion

The scenarios and case studies illustrate the capability of the stochastic scheduling tool. It achieves its goal of minimising the energy bill payments of customers. The combination of the rolling planning technique and the two-stage RTP scenario tree enable frequent electricity price forecasting for scheduling the household at each planning loop. The scheduling results of the devices change if the prices in a single planning loop are different. The change of prices in a single loop will also influence the prices in the following loops, which may result in a change of scheduling results. This can be observed by comparing the prices and scheduling results of scenario 1 and scenario 2. Thus, customers can flexibly react to the changing dynamic prices, with the aid of the stochastic tool.

Furthermore, by including the external notification before making the decision at the beginning of every single loop, the stochastic scheduling tool helps customers to adapt to the dynamic network conditions (reflected by the prices). In this way, actively participating consumers can help with reacting to certain network problems through the price signals notified by operators/ aggregators. Therefore, the stochastic tool is capable of coordinating active participation households with operators/ aggregators, through the price signals. At the same time, the stochastic scheduling tool benefits consumers with energy bill savings when they are exposed to stochastic dynamic energy prices.

Energy bill costs of the scheduling results from the stochastic tool and the basic tool are compared in Table 6-1. If the basic tool is used (i.e. the household sticks to the scheduling results based on forecasted RTP rates for the next 24 hours without rolling optimisation), when it is facing the stochastic pricing scenarios (scenario 1 and 2), the energy bill payment is calculated and recorded in the 'The basic tool (RTP)' column in the table. The energy bill payment costs of the basic tool are computed by using the scheduling results of RTP in House B, D and G (in section 4.3 in Chapter 4) and the price scenarios (scenario 1 and 2) in this chapter.

It can be observed that the energy bill payment of House B, House D and House G are lower when it is scheduled by the stochastic tool. House D has the lowest bills comparing to the other two houses, because of the PV production. House G has the highest bills, as it has the most number of devices connected. The bill payment difference between the basic tool and the stochastic tool is larger in House G. This is because House G has a higher power consumption allowance of 10kW, which allows more energy shifting space for the high consumption devices in the house, when comparing to the 5kW limit in House B and House D. As a result, after employing the stochastic tool and enabling customers to be more flexible when corresponding to the stochastic prices and external notifications, the houses pay less under the rolling planning price scenarios.

Table 6-1 Energy Bill Cost Comparisons

Bill Payment Comparison			
House B	*The basic tool (RTP)*	*The stochastic tool (rolling planning)*	*Difference*
Scenario 1	20.66¢	19.63¢	1.03¢
Scenario 2	22.31¢	21.34¢	0.97¢
House D	*The basic tool (RTP)*	*The stochastic tool (rolling planning)*	*Difference*
Scenario 1	11.89¢	10.57¢	1.32¢
Scenario 2	12.41¢	11.12¢	1.29¢
House G	*The basic tool (RTP)*	*The stochastic tool (rolling planning)*	*Difference*
Scenario 1	24.94¢	21.99¢	2.95¢
Scenario 2	26.11¢	23.01¢	3.10¢

6.4. Summary

This chapter has proposed a stochastic scheduling tool that is able to help customers coping with the rising stochasticity coming from energy prices. The stochastic scheduling tool enhances the basic scheduling tool presented in Chapter 3. It combines the forecasted two-stage RTP scenario tree and rolling planning technique, which has been introduced in section 6.3.1 and section 0, respectively. Detailed steps of constructing the two-stage scenario tree have been presented in Chapter 5. The mathematical formulation of the stochastic scheduling tool are given in section 6.3.2. The stochastic tool considers end-users' energy consumption patterns and preferences, and helps consumers to achieve energy bill savings intelligently. External notifications are also involved in the stochastic scheduling tool on the basis of rolling planning, which can be sent from network (system) operators/aggregators. By including external notifications, the stochastic scheduling tool coordinates network operators and actively participating consumers' responses, to assist network operation while their energy usage preferences are respected at the same time. Customers are also able to react to dynamic prices and adapt to stochastic network conditions.

Case studies of the stochastic scheduling tool have been carried out in virtual house models (House B, House D and House G) in section 6.3.3. Detailed steps of the application of the stochastic tool in the case study have been introduced in section 6.3.3.1, together with case study results discussed in section 6.3.3.2. Two different price scenarios (with different alterations due to external notifications) have been tested in the stochastic tool. The case studies have shown the stochastic scheduling tool succeeds in achieving its goal of minimizing customers' energy bill cost. Furthermore, a comparison of the bill costs between the basic tool and the stochastic tool is made in section 6.3.4. Therefore, the stochastic tool makes it possible for aiding consumers to monitor the electricity price signals intelligently, reacting to the network operators' requirements and achieving energy bill savings automatically.

If a customer is willing to provide flexibility to network operation by actively reacting to incoming price signals (either stochastic RTP or external notifications from network operator), they will find the stochastic tool is very useful. This is because the stochastic tool position customers in a better place when they are facing changing prices. Customers can receive cheaper energy bills by actively responding to the prices.

Chapter 7

Conclusions and Future Work

7.1. Conclusions

Demand Side Management (DSM) can provide flexibility to the grid operation, which is presently an urgent need, considering penetration of renewable energy and Distributed Energy Resources (DERs), such as energy storage and solar panels. During recent years, consumer's awareness and understanding of energy usage have increased. Moreover, prosumers who can produce energy for self-use and/or export to the grid, e.g. solar panels, are starting to emerge. However, survey data summarised by Ofgem [136] advises that the overall usage pattern of domestic customers engagement in 2016 is largely unchanged relative to 2015 and 2014 in the UK. These suggest a huge opportunity for DSM to help domestic consumers and enable customers to provide flexibility to network operation.

There have been DSM trails on domestic consumers in the UK, such as the NINES project [82] carried out by Scottish and Southern Electricity Network. The control of the NINES trial is based on Direct Load Control (DLC), which schedules consumers' devices directly by sending out frequency signals to individual appliances after acquiring consumers' consents. Although DLC is a straightforward way for network operators to schedule the home appliances, it may discourage consumer's participation due to perceived intrusiveness.

This thesis has developed novel customer-centred self-scheduling tools (a basic and a stochastic tool) that schedule consumer's home appliances based on their energy usage behavioural preferences. The preferences are assessed through investigating the scheduling flexibility levels of the devices, and also considering social aspects summarised from surveys. In contrast to the DLC, the customer-centred self-scheduling concept prioritises customers' willingness and energy usage preferences.

The aim of the scheduling tools is to minimise the energy bill payment of customers, through scheduling home appliances according to various pricing signals. Meanwhile, consumers' electricity usage preferences are respected during the scheduling process. The tool also gives consumers choices and options to choose if they are willing to participate and how much they are going to taking part in the program, by indicating the availabilities and running time durations of the home appliances. Network/system operators can utilise demand side flexibility by sending various price signals to different households, The scheduling tools will be able to schedule appliances based on the price signals, customers therefore can assist network operation.

The developed basic scheduling tool has been tested in seven virtual household models, which have appliances selected from different scheduling flexibility categories and various DERs (e.g. energy storage, EV and solar panels). Time of Use (ToU) pricing (Economy 7) has been tested in these seven household models. The scheduling tool optimises the activities of the home appliances and the utilisation of the DERs. Take the PV panels as an example, it schedules if the PV production will be self-consumed or exported to the grid for extra income. In addition to ToU pricing, dynamic Real-Time Pricing (RTP), which can reflect certain network conditions, has also been tested as the second type of pricing signal into the basic scheduling tool. Stochastic RTP rates were forecasted by using Auto-Regressive Moving-Average (ARMA) time series model, based on PJM historical RTP data. This is because ARMA is robust, efficient and flexible, which can fit into various kinds of databases for relatively good forecasting results.

Additionally, a stochastic customer-centred scheduling tool, which enhances the basic scheduling tool, has been developed to incorporate the dynamic customers' responses and rising stochasticity coming from the network, where the rising uncertainty is indicated through the incoming dynamic price signals. The stochastic scheduling tool combined the established two-stage scenario tree (based on RTP forecasting, scenario generation, scenario reduction and validation steps) and the rolling planning technique with the basic tool. The rolling planning divides the overall planning horizon into several equal time intervals, and a new plan is generated at the start of each time interval. Therefore, the stochastic scheduling tool considers short term and long term planning at the same time. The research further improves the rolling planning technique by including scenario trees and external price notifications. At the beginning of every single planning loop, if there is external price notification sent from network (system) operators/aggregators, the price signal in the planning loop will be revised accordingly. Case studies of the stochastic scheduling tool have been carried out in different house models.

To summarise, a customer-centred scheduling tool has been developed in the research to help consumers corresponding to incoming pricing tariffs based on consumers' willingness and scheduling preferences. In addition, a stochastic scheduling tool has been proposed by enhancing the basic scheduling tool. The stochastic tool coordinates network operators and active consumers' responses. Therefore, the consumers are able to aid network operation and provide certain flexibility, while their energy usage preferences are respected at the same time. With the optimisation functionality of the stochastic scheduling tool, customers can also achieve minimised energy bill costs when they are facing stochastic energy pricing.

7.2. Future Work

This research has proposed simulated scheduling tools that are able to help active participate energy consumers to respond to dynamic pricing, on the basis of consumers' energy usage preferences. The stochastic scheduling tool also involves consideration of assisting customers to adapt to the uncertainty coming from the power system, which allows end-users to aid network operation by providing certain demand side flexibility and to achieve energy savings when facing stochastic real-time energy prices. But it is recognised that the following recommendations of future work should be considered:

- Enhancement of the customer-centred scheduling tools: Enhance the tools with longer scheduling horizons, smaller scheduling time intervals, and also test the tools with different parameter configurations, in order to reflect more realism
- Practical implementation and validation: Before trial the developed scheduling tools in real world, hardware implementation can be tested first, as one way to validate the optimisation algorithm proposed in this research
- Aggregation of dynamic demand responses: One way to manage aggregated dynamic consumer responses and to harness the flexibility stemming from the dynamic customer behaviours.

These further work could provide additional benefits and overcome limitations of the research. In the following sections, specific areas of the future work are discussed together with descriptions of potential solutions and methods that could be applied, including possible beneficial outcomes.

7.2.1. Enhancement of the Customer-centred Scheduling Tools

The basic scheduling tool has been tested in seven virtual house types to prove the scheduling capability with home appliances under different scheduling flexibility levels, energy storage, EV, storage heater and solar panels. The charging and discharging activity of the energy storage device are optimised during the scheduling process, and the energy produced by the solar panels is decided if it will be self-consumed or export for extra earnings. Furthermore, the energy storage and the PV supplies part of the energy used for charging the EV and the energy storage, and their charging activities are optimised.

In addition, the stochastic scheduling tool is tested in three of the seven houses (House B, House D and House G) with home appliances and various DERs. The behaviours of the simulated devices are scheduled according to stochastic RTP.

Appliances and devices in the virtual households can be tested with a different set of parameters, such as minimum operating time and maximum off time. Moreover, considering the EV and energy storage device simulated, different configuration can be tested. For example, the energy storage can has additional limitations on the depth of charge, charging/discharging efficiency, and charging/discharging cycle limit per day etc., which are technology specific.

Both of the customer-centred scheduling tools can be enhanced by adding more home appliances, through investigating the characteristics and behavioural patterns of various electrical devices. Especially for the small home devices considered as high scheduling flexibility, which have built-in batteries, e.g. laptops, mobile phones, etc., can be modelled in the tool. The optimised utilisation of these rechargeable batteries can provide further flexibilities to network operations. Moreover, more medium and low scheduling flexibility home devices can be scheduled as well.

In addition to the enhancement of adding more home appliances, the scheduling time interval can also be smaller. The current scheduling tools are simulated for the time interval of 1 hour for a total of 24 hours a day. Through using a smaller time interval during the scheduling process, home appliances can be operated within a shorter time scale. For the devices requires running for more than an hour and for appliances have minimum running hours, the continuous operating constraints will still apply. However, it should be noted that under a shorter scheduling time interval, the home devices are less likely to be switched on and off several times in a short period, which will affect the operational life of the devices adversely. This can be enforced by additional devices’ operating constraints embedded in the scheduling tools.

7.2.2. Practical Implementation and Validation

Another area of future work is physically-based modelling of the customer-centred scheduling tools. The simulation case studies carried out in this research has proved that the scheduling tools can bring benefits to both customers and network operators. Application of the scheduling tools in a physically-based model can test its capability in a real-world environment, especially on the communication aspect.

A physically-based DR residential load model is presented in [137], which models space cooling/heating, water heating, clothes drying, and Electric Vehicle (EV) loads. The physical DR model controls the devices based on the variation of temperatures in the house for space cooling/heating, the water temperature in hot water tanks for water heating, direct control signals for cloth drying, and driving patterns for charging and discharging activities of an EV battery. Moreover, an energy management system is proposed in [138] with smart meters and smart domestic appliances. The energy system is tested with Raspberry Pi and smart plugs, where Raspberry Pi is used as a getaway and smart plugs control the appliances.

There are various ways to build a physically-based framework for testing the scheduling tools. In addition to the methods reviewed and assumed in this research, i.e. using smart meters for two-way communication enabler so to assist the control of the home devices. A further hardware implementation of the scheduling tools could verify the capability of the tools. Moreover, the results from simulations of the tools and testings of physically-based models can be used to evaluate the gap between theoretical study and actual implementation. This would help with producing a design that is more suitable for real-world implementation.

7.2.3. Aggregation of Dynamic Demand Responses

It is expected that the active participated consumers' responses vary from different households. One way to manage such dynamic responses, and also to harness the flexibility stemming from the dynamic customer behaviours, is to aggregate customers' responses/flexibilities. The aggregation can be carried out by the network (system) operator or an independent aggregator (third party) that seeks to use/sell demand flexibility services. Aggregators can send signals to their consumers to modify their demand as a response to the System Operator requirements and/or market price signal [139]. There exists a number of opportunities that aggregators can participate in the UK, including balancing mechanism, wholesale market, and capacity market etc. [139]. The opportunities give strong evidence that demand responses can be deployed by aggregators, and demand response aggregators can provide flexibilities to markets.

When it comes to the aggregation of customers' flexibilities, the home appliances are normally aggregated through different categories, depending on the characteristics and patterns. For example, [54, 140-142] illustrates the aggregation models for Thermostatically Controlled Loads (TCLs), where [54, 140] focuses on electric water heaters and [141] models air conditioners. The aggregation of electric water heater is made through modelling of a single heater and using a rejection type Monte Carlo simulation of random parameters within a specific range. Similarly, an individual physical model of TCL is built first in [142]. Based on the individual model, a second-order aggregated model is developed in [142] that considers both statistical information of the population and dynamic mass temperature in the buildings. In contrast, [141] starts from a population of air conditioners. Through the regulation of temperatures, the aggregated power consumption of the air conditioners is described by the varying operation of them.

Considering the aggregation of the customers' responses using the scheduling tools, one can run the scheduling tool in parallel with different settings from customers so to aggregate a sample of group responses. However, this may only represent a small portion of the dynamic customers' responses. Since this is a model-based planning problem in which aggregation plan changes in response to the behaviour changes, AI planning techniques [143] can be one of the appropriate approaches to be used for aggregation.

Appendix I
DSM Trial Results and Findings

DSM trials in the US, EU and UK are reviewed in details in the following sections.

i. Olympic Peninsula Project

Olympic Peninsula project was a field test project carried out as part of the Pacific Northwest GridWise Testbed demonstration project, which was led by pacific northwest national laboratory [75]. The field demonstration took place in Washington and Oregon. The project started planning in late 2004 and finished in 2007.

The Olympic Peninsula project tested different energy pricing strategies to end users, such as fixed rate tariff, ToU tariff, and RTP tariff. It also used two-way communication between the grid and Distributed Energy Resources (DERs) which enabled the dispatching of DERs based on the price signals they receive. The DERs included in the Olympic Peninsula project were five water pumps with a total power of around 150kW, two distributed diesel generators (175kW and 600kW) and 112 residential households. The 112 homes were divided evenly across the three energy pricing tariff and one control group. Electric space heating and water heaters in the 112 households were controlled via the two-way communications. The space heating devices had both heating and cooling functions.

The scheduling experiment of residential households lasted for one year. Participated customers were offered an average of $150 incentive payments depending on their responses to the control signals. As Figure I-1 [144] shows, customers can view schedules of the home devices and management of their energy consumption. The scheduling preferences could be set by customers through this programme. Moreover, there were automatic options available to customers, i.e. customers can simply choose the goal of the scheduling whether to achieve the most energy bill savings or to reach maximum comfort, etc. Detailed energy consumption could be viewed on a single device level. As part of the 112 homes were allocated to a control group, these customers can only set their occupancy modes and set points of the corresponding thermostat. The control group received $150 cash earnings without assessing how they manage their energy.

Besides the incentive payments made to residential customers, monthly savings of customers were calculated during the project time. The savings referred to the difference between the incentives and the energy bill payments. Customers with fixed rate energy pricing had 2% savings, and over half of this group had no savings. Customers assigned to the control group had no savings. Customers with ToU pricing and RTP had 30% and 27% savings, respectively. It is worthwhile mentioning the average amount of savings per month of RTP customers were higher than ToU customers although ToU customers had a higher percentage of savings.

One of the key findings of the Olympic Peninsula project was the residential thermostatically controlled load reacted to the RTP, and a significant shift was observed in energy consumption, as shown in Figure I-2 [75]. The RTP was directly responsive to the market price, and it was observed to be the most effective in shifting thermostatically controlled load among the energy pricing tariffs used. The load succeeded in using lower prices periods during early morning before 6 am and late night after 9 pm. The load shifting was achieved no matter if the feeder is constrained or not, but it can be concluded that the load shifting could contribute to release limits when the feeder is constrained. The peak load was reduced as a result of load shifting.

This showed customers are able to actively participate in DSM programs with the control (i.e. to save money or increase comfort level, etc.) still remained with them.

The Olympic Peninsula project estimated that a 5% reduction in peak load was achieved under a 750kW feeder constraint, 20% peak load reduction was easily obtained under a 500kW feeder constraint. The project achieved 19% and 29.7% average peak reductions for the 750kW and 500kW constraints, respectively, during the project time [75].

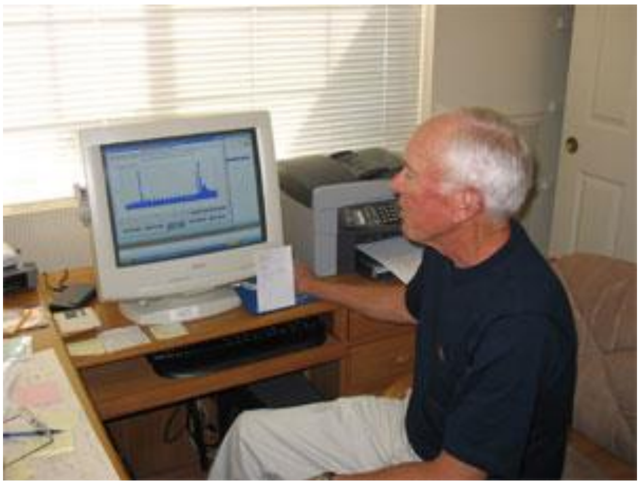


Figure I-1 A Customer Monitors Energy Costs and Usage from His Home Computer [144]

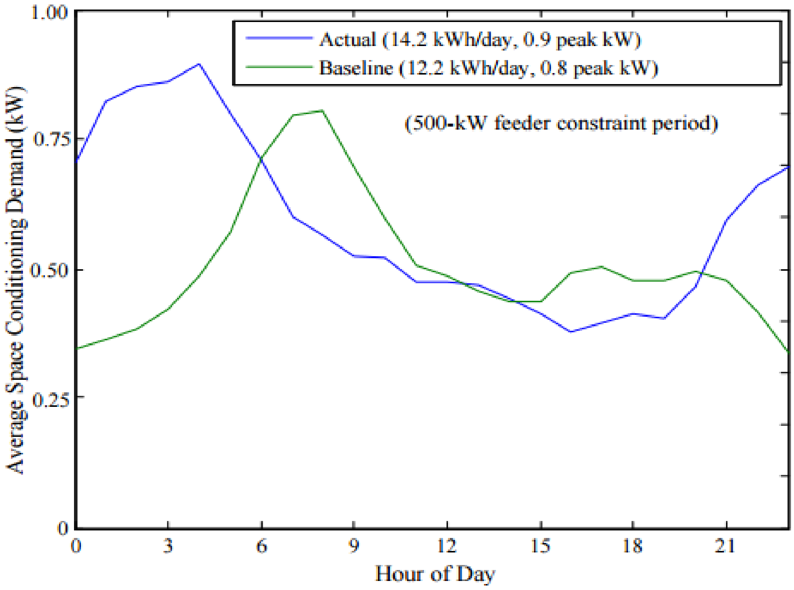


Figure I-2 Shifting of Thermostatically Controlled Load by Price [75]

ii. ADDRESS Project

The Active Distribution network with full integration of Demand and distributed energy RESourceS (ADDRESS) project was framed in the European smart grid concept, with its vision for the future electric network on flexibility, accessibility, reliability and economy [77]. 25 partners located across 11 European Member States were involved. The project started on 1st June 2008 and ended in 2013, which lasted for 5 years.

The ADDRESS project aimed to develop solutions to enable active demand and exploit benefits of active demand. It also involved prosumers, who consume and produce energy. The project proposed solutions to achieve full integration between active demand, DGs, and renewable resources, so to engage domestic and small commercial customers in the power system. The proposed solutions were validated in 3 test sites located in France, Italy, and Spain.

A role of aggregator had been applied in the ADDRESS system, who sat between markets and consumers. The aggregator was responsible for sending signals to consumers, optimising the demand usage, interacting with market participations, and participating in the market [145]. Moreover, the application of ADDRESS system was different in each test sites. As Figure I-3 [146] shows, a full ADDRESS system had been tested in France, with Spain and Italy test sites tested on separate levels of the system. The Italy field test focused on the upstream part of the ADDRESS system from the players of the electric system to aggregators. While the Spain field test focused on the downstream part of the ADDRESS system from the aggregator to individual consumers. The Italy test site included a 1MW 0.5MWh energy storage system [147].

The ADDRESS project considered social aspects that impact customers' engagements. Questionnaires were distributed to customers participated in ADDRESS at the early stage of trial, which benefited the project with a better understanding of the factors that may influence the customers' willingness to accept ADDRESS technology. The questionnaire asked participants' knowledge of environmental and other sustainability issues, awareness of their energy consumption and patterns, participants' motivation and perception of ADDRESS technology benefits, as well as their expectations of living with ADDRESS [148].

Three standardised active demand products raised in the ADDRESS project are summarised in Table I-1[145]. According to [145], an active demand product was what the aggregation function provides or sells to the other participants and which they use to meet their needs. The active demand product modified the shape of the demand curve and the product was provided during a specific duration. An Energy Box (EBox) was installed to enable communications between aggregators and appliances. Customers received combined price and volume signals (as presented in Figure I-4 [145]) from the aggregation function, so their consumption patterns are changed ('re-profiled'). Since test sites in France and Spain involved customers, EBox were installed in these two test fields. The scheduling of appliances in ADDRESS project divided the devices into manageable loads and non-manageable loads [149]. Manageable loads included air conditioning and washing machine etc., and non-manageable loads included refrigerator, lighting and etc. The EBox optimised the scheduling of appliances, which maximised the function of the customer [150]. The functions were to minimise energy bill cost of customers and maximise customers' comfort level. Smart plugs were installed and connected with EBox to control traditional appliances. Appliances enabled with smart functions could be controlled directly by EBox.

Table I-1 ADDRESS Active Demand Products and Main Characteristics [145]

AD Product	Conditionality	Typical example
Scheduled re-profiling (SRP)	Unconditional (obligation)	The aggregation function has the obligation to provide *a specified* demand modification (reduction or increase) at a given time to the product buyer.
Conditional re-profiling (CRP)	Conditional (real option)	The aggregation function must have the capacity to provide *a specified* demand modification during a given period. The delivery is called upon by the buyer of the AD product (similar to a reserve service).
Bi-directional conditional re-profiling (CRP-2)	Conditional (real option)	The aggregation function must have the capacity to provide *a specified* demand modification during a given period in a bi-directional range [-y, x] MW, including both demand increase and decrease. The delivery is called upon by the buyer of the AD product (similar to a reserve service).

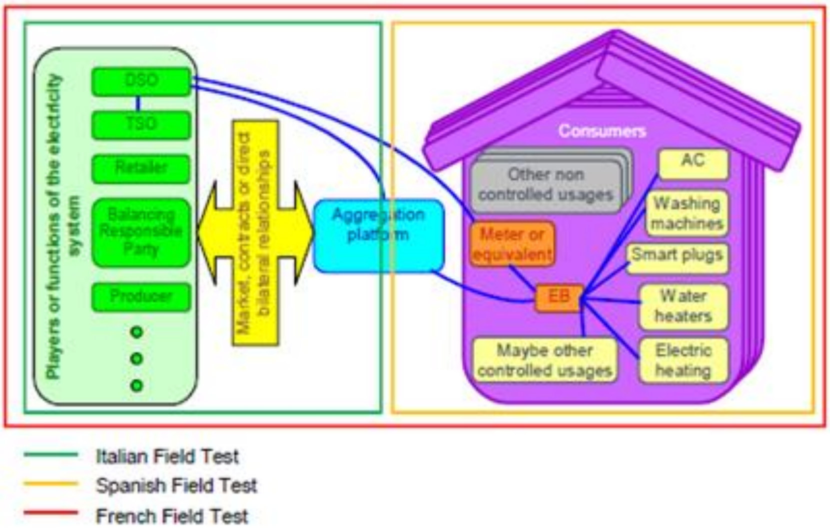
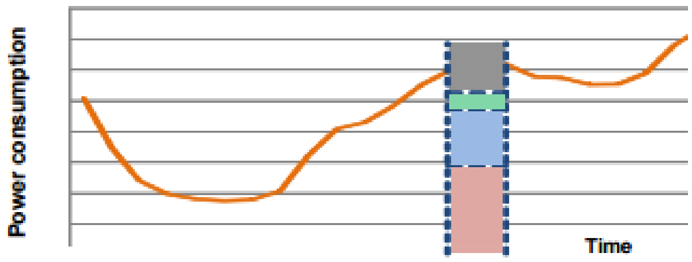


Figure I-3 The ADDRESS Field Tests Systems [146]



	Average power consumed over time period	Price
	Less than 0,6 kW	Incentive of X (€)
	0,6 kW ≤ Power < 0,95 kW	Incentive of Y (€)
	0,95 kW ≤ Power < 1,05 kW	Incentive of Z (€)
	More than 1,05 kW	Incentive of W (€)

Figure I-4 Example of Combined Price and Volume Signals Received by Ebox for Triggering Consumer Responses [145]

The behaviours of smart plugs are presented separately in Figure I-5 [147] in a working day and a holiday. The target of the smart plugs was to decrease consumption during evening peak time of a working day and to increase usage during a specific period of a holiday day. It can be observed in Figure I-5 that the smart plugs scheduled the controllable demand to fulfil the target in response to AD (Active Demand) signal. The EBox received the request of active demand from aggregator, one example of the corresponding customer responses are shown in Figure I-6[147]. Active customers received a request to reduce their consumption during the morning peak from 7.45am to 8.15am on 14th March in the French test site. An average reduction of over 700W per customer was achieved on that day.

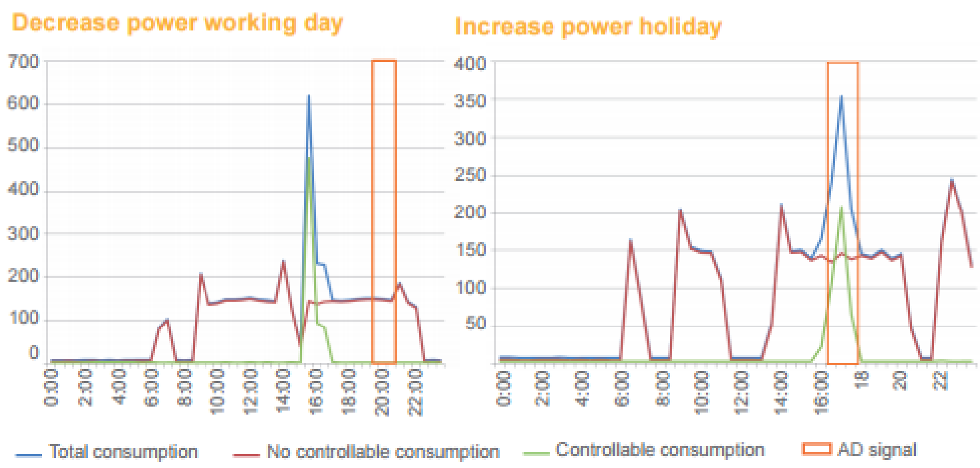


Figure I-5 Behaviours of the Smart Plugs [147]

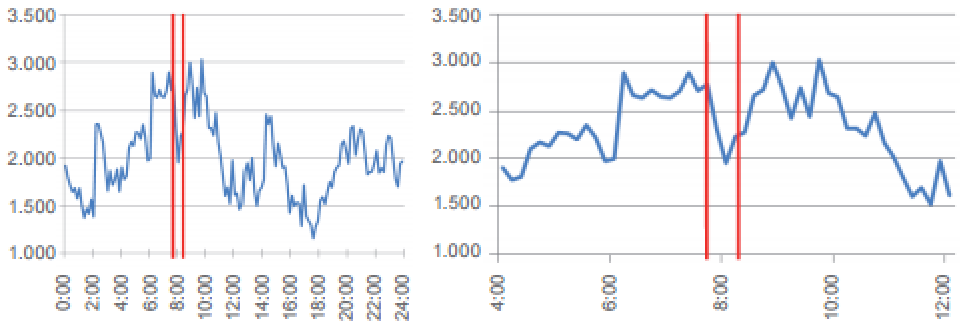


Figure I-6 Average Consumer Response During the Morning Peak Period [147]

iii. NINES Project

The Northern Isles New Energy Solutions (NINES) project was carried out by Scottish and Southern Electricity Network (SSEN), as one of the UK's Distributed Network Operators (DNOs) [82]. The NINES project started in 2010 and its aim was to present an integrated plan to manage supply and demand on Shetland. The Shetland Islands are not connected to the main GB electricity network and, as such, face unique electrical challenges – but also a unique opportunity to decarbonise supply. The objectives of NINES were to:

- o a reduction in maximum demand; and
- o a reduction in the electricity units generated by fossil fuels.

Assets enabled in the NINES project include a 1MW 3MWh valve-regulated lead acid battery, 5 renewable DGs with a total capacity of 8.545MW, and 234 domestic households. An overview of the NINES elements is given in Figure I-7 [151]. The project employed Active Network Management (ANM) system developed by Smarter Grid Solutions [152] to monitor different parameters affecting the network, including embedded constraints, frequency stability and weather, and to manages an appropriate response. Existing generators on the Shetland was integrated as well, these included conventional (Lerwick power station and Sollum Voe Terminal) and wind (Burradale and Ollaberry) generators. A key driver for the trial had been to develop an understanding of how these technologies work and interact in a real-life environment.

This project worked in partnership with Hjaltland Housing Association, who contracted with Glen Dimplex to install new DSM compatible heating systems in 234 homes on Shetland, and SSEN arranged for a communications and management system to be installed to manage the energy demand of these appliances. The DSM compatible heating systems installed in the 234 homes including water and space heaters to store energy in the form of heat. These energy storage appliances can receive remote signals every 15 minutes through the Domestic Demand Side Management (DDSM) communication infrastructure, and thus allowed a more flexible energy consumption by changing the delivery and amount of energy that was required at different times of the day. The remote signals that the DDSM appliances received instruct them when to operate, while also enabling them to send feedback information regarding their status, e.g. if they were charging, were on stand-by, were switched off, etc. This communication and control enabled the DDSM homes to provide capabilities for demand side management. Moreover, the installed heating devices were frequency responsive, so that they can, automatically and independently of signals sent by ANM, stop charging if the system frequency drops, or start charging if system frequency rises above the specified limits. Thus, the frequency responsive heaters can help system operator maintain the balance between the demand and supply and therefore, maintain system frequency and security.

In addition to following signals sent by Shetland power system operator through the ANM system, the appliances were also enabled to consider the comfort level of occupiers in the households. These DSM–capable devices were configured to be switched on when the room temperature reaches the minimum level set by the users, but also to be automatically switched off for safety when the maximum cut-off temperature is reached. Based on the energy use during the previous day, and in order to ensure the specific comfort level required by each participating DDSM household, an algorithm embedded within the heating devices calculated the daily energy requirements for each device for the next day.

SSEN had been engaging with the DDSM customers under its engagement plan throughout the lifecycle of the NINES project. 6 core methods were used to engage with domestic customers directly, which include: issue payments (as incentives for participation), website updates, hosting of local meetings, issuing of written communications, phone calls to customers, and carrying out of home visits. Financial incentives were offered to initially joined customers when they consented to continuous collection and analysis of data by SSEN. A one-off payment of £100 was payable to the participated customers 6 months after installation and sign up, under the condition that the data collection process was allowed for at least 6 months. An additional £50 was paid to the existing customers that agreed to install independent monitoring. New customers will only be encouraged by knowing that they are helping to reduce fossil fuel emissions by participating.

As social housing has a relatively high turnover in occupancy, and this has a continuing impact on the overall number of consented properties at any point in time as with each change in tenancy comes the need to obtain consent and agreement from the customers for their heating requirements to remain under the control of the ANM. Though this fluctuation of occupants has created a number of administrative challenges, throughout the project SSEN have continually tried to engage with the new tenants who have moved into these properties, although in some cases not all of the customers responded. Thus, at the time of the report [153], 223 DDSM households, distributed throughout the Shetland Isles, remain in the scheme. The geographical locations of the 223 DDSM homes are illustrated in Figure I-8[153] and summarized in Table I-2 [154]. The majority (78%) of the rollout houses were in the centre and south of Shetland Mainland, with 63% in the main towns of Bressay and Scalloway. Due to the concentration of DDSM homes in the central towns, most of these houses were supplied by just two substations. However, given that all the DDSM houses were already electrically heated, and the original heaters were replaced by new Dimplex heaters as part of the NINES project, there was unlikely to be additional loading on any of the substations.

Over the 3.5 years roll-out period during the project, the total cost of the DDSM scheme and support services is £3.2 million, which is shared between SSEN and HHA, with 64.8% of the total cost covered by SSEN. In addition, there will be ongoing operational cost of £491k per year for providing services to the DDSM customers under the current scope (i.e. 234 DDSM households) after the end of the project.

Besides the incentive payments made to the DDSM customers, it was concluded in [155] that moving houses to flexible DDSM trial from teleswitching reduced their maximum possible load at peak times by 0.5MW, if the devices followed schedules. Existing teleswitching customers would see 10-18% lower heating consumption and better regulation of temperature. In addition, the DDSM flexible customers had alleviated curtailment of 77MWh of renewable energy (generated by two of the renewable DGs, North Hoo and Luggie's Knowe), during the period of February 2016 till January 2017 [153]. This would correspond to North Hoo and Luggie's Knowe asset owners receiving additional FIT payments of £6,261.83 and £4,101.83 respectively. In addition, the alleviated generation that would otherwise have been curtailed saved £11,621.65 of conventional generation costs.

Following the calculation of the renewable energy benefits, a cost benefit analysis had been conducted in [153] to illustrate the costs of achieving the benefits enabled by the DDSM flexible customers. A cost value of using the DDSM flexible customers to

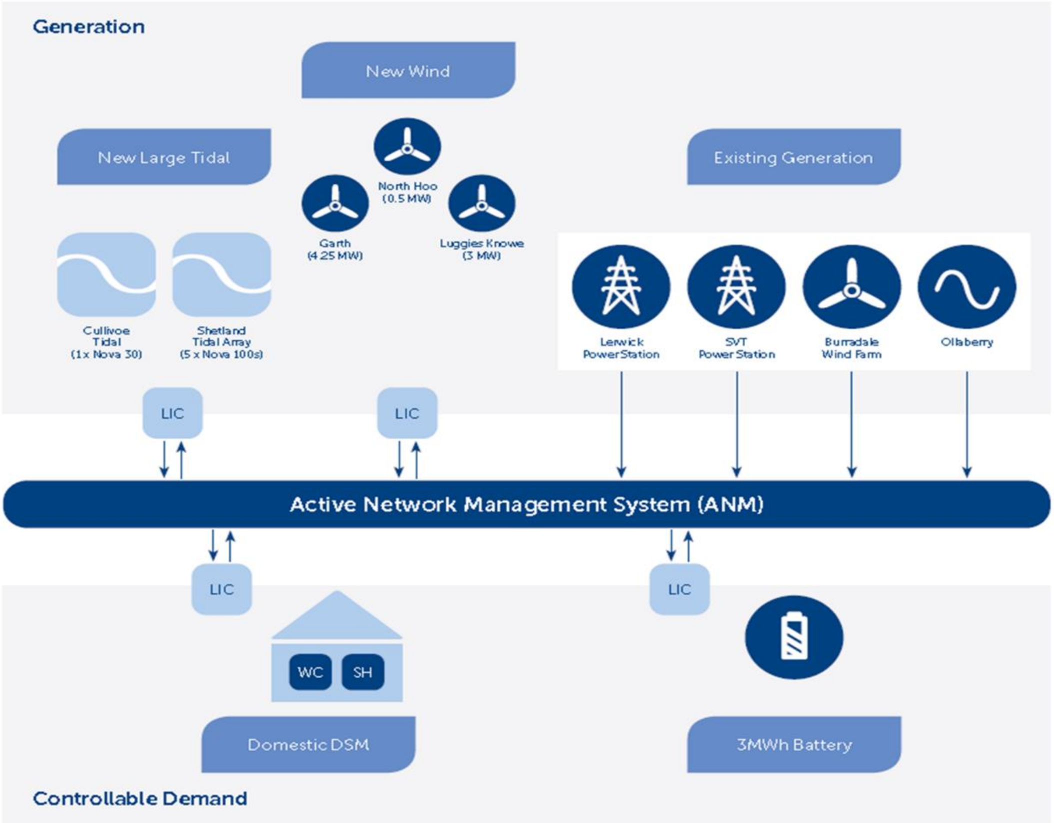


Figure I-7 Overview of NINES Elements [151]

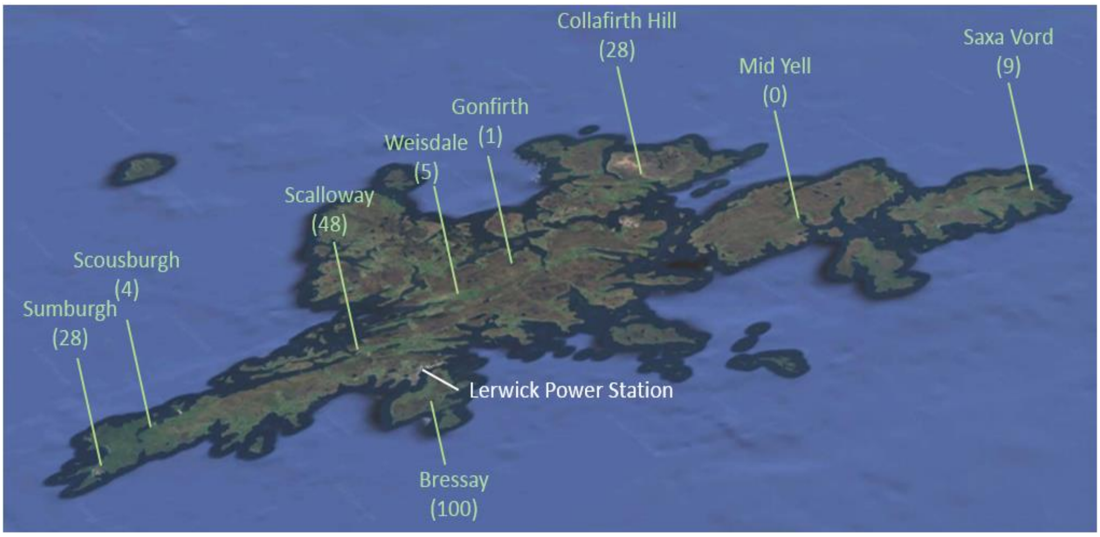


Figure I-8 Geographical Locations for DDSM Households on Shetland [153]

Table I-2 Geographical Distribution of Rollout Houses [154]

Area	Community	Houses
Centre	Bressay, Lerwick, Scalloway,	141
South Mainland	Burra, Cunningsburgh, Scatness, Virkie	34
West Mainland	Bixter, Sandness, Walls	14
North Mainland	Brae, Sullom	11
North Islands	Unst, Whalsay	23

avoid the 77MWh renewable energy curtailment was determined as £7,360.40/MWh. During the evaluated period from February 2016 to January 2017, part of the flexible customers helped alleviate renewable energy reduction since 26th September 2016. Thus, the renewable energy curtailment alleviation was expected to be 105.7MWh if all the flexible DDSM customers had provided flexibility for a full year, through assuming the same percentage of flexible customers heating capacity was used for alleviating renewable curtailment. The cost of using flexible customers reduce renewable energy curtailment was therefore reduced to £5364.75/MWh.

The total available flexibility of the heating devices (installed in the all flexible DDSM households), was estimated to be a total of 1GWh per annum. This value of 1GWh was calculated based on the energy requirements of the flexible customers. Considering the rules by which DDSM operated mean that, wherever possible, appliances in the flexible charging groups are scheduled to apply primarily at times that NINES connected renewable generators would otherwise be curtailed. If the scheduling of flexible customers heating devices perfectly aligned with renewable curtailment, the future cost of using these DDSM flexible customers to reduce renewable curtailment would be lower, at £560.94/MWh. As the NINES Project had now officially closed there was no possibility of adding to the number of customers participating in DDSM. In theory, however, if more homes were participating this would lead to more alleviation of otherwise constrained renewable generation which in turn would lead to a reduction in the estimated cost of renewable energy curtailment noted above.

Appendix II
Electricity Price Forecasting Methods

Major electricity price forecasting methodologies are reviewed briefly in this section, which are Artificial Intelligence (AI) method (artificial neural network) and time series models (transfer function and Auto Regressive Moving Average (ARMA)).

i. Artificial Intelligence

Artificial Intelligence (AI) uses intelligence by machines so to mimic human minds. AI forecasting methods involve learning processes to map the input-output relations and adapting to systems, especially non-linear and complex systems. The ability to solve complex systems is one of the advantages of AI approaches, and it includes a diversity of intelligent tools.

Artificial Neural Network (ANN) is one of the commonly applied categories of AI methods, including feedforward and feedback networks [103]. The ANN constructs interconnected units and presents related objects through learning from sample data [156]. It is able to correlate the sample data even if the data relationship is unclear and complex. Figure II-1 [156] presents an example of 3-layers feedforward ANN model with n inputs, m hidden, and 1 output nodes. By inputting the sample data into an ANN model via the input nodes, the data information is trained through the units several times. After the training, ANN determines the relationship between input and output, and the output of the ANN model is compared with a reference target. The aim is to minimise the difference between the ANN model output and reference target. This difference can be calculated as a mean square error term. In order to acquire a minimised error, the ANN model learns to adjust the weights of the units (between input layer, hidden layer and output layer) during the iterations of the learning/training process. When the error converges to a pre-set range, the iterations process stops.

Feedback ANN models can cope with dynamic systems, as the outputs are computed based on the input pattern. The feedback enables modification of inputs. Elman model, as one of the general feedback ANN model, as shown in Figure II-2 [157], has an additional 'context layer'. The 'context layer' is connected to the hidden layer and it can preserve historical information. Example applications of Elman model in electricity price forecasting can be found in [157] and [158].

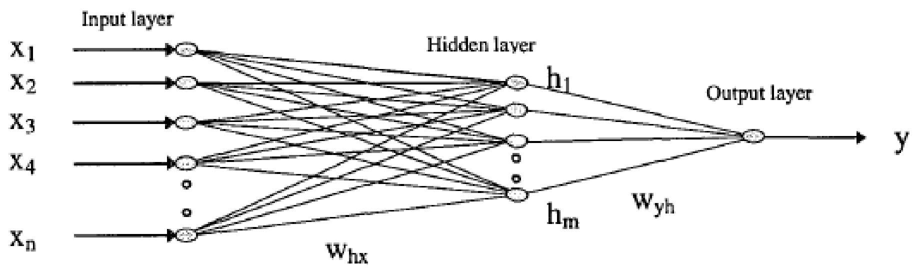


Figure II-1 Generic Example of a 3-layers Feedforward ANN Model [156]

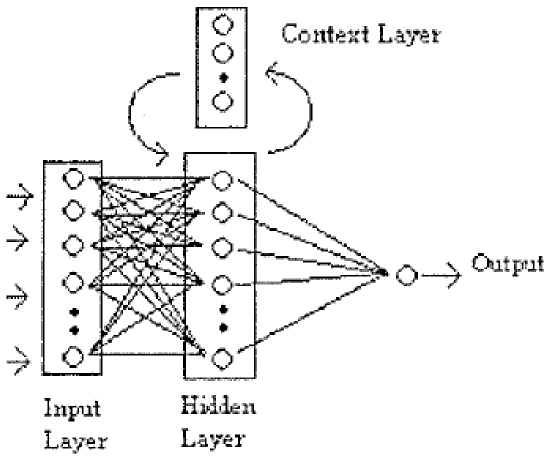


Figure II-2 A General Feedback Neural Network Model, Elman Model [157]

Two typical ways to improve ANN forecasting performance are i) increase learning cycles and ii) improve/pre-process input data with chosen factors. One of the training processes of the ANN model is to decide the number of iterations performed throughout the learning of sample data. It is concluded in [156] that the learning results gradually improved in the network prediction ability with an increasing number of cycles. However, a large number of cycles may also indicate over-fitting of the sample data, which may result in generalised input parameters. Furthermore, the accuracy of the forecasting result of ANN model can be enhanced by analysing the impact of different factors on the electricity prices [159]. Pre-processing input data to include relevant information can help improve forecasting results, e.g. inputting chosen factors of a similar day [160] and adding demand data [161] for forecasting electricity price through ANN.

AI forecasting methods are known as their ability to handle complexity and non-linearity, as their major strength [103]. However, data over-fitting will influence the forecasting results. In addition, due to the AI technology has a wide range of tools available, it can be difficult to compare performance between different tools, in order to find an optimal solution with diverse choices of AI approaches.

ii. Time Series Models

As defined in [104], a time series is *'a sequence of observations taken sequentially in time'*. Time series models are specially developed to analysis sequentially observation data occurred during a time series, and one of the features of a time series is adjacent observations are dependent. Time series analysis requires the development and application of dynamic models for time series data.

Transfer function model can reflect the dynamic relationship between a continuous time series input and a continuous time series output. A general form of the transfer function is expressed in equation $(\mathrm{II}-1)$ [104], which shows a dynamic linear relationship between input $\mathrm{X_t}$ and output $\mathrm{Y_t}$.

$$\mathrm{Y_t} = \mathrm{v(B)\,X_t} \qquad (\mathrm{II}-1)$$

where coefficient $\{v_j\}$ is a hypothetical impulse response function, and B is backshift operator $Bz_t = z_{t-1}$.

The dynamic relationship is dominated through $\{v_j\}$, and both past values of X_t and Y_t may be used in forecasting. For the case of electricity price forecasting, detailed introduction and development of applying a transfer function model to forecast electricity prices are given in [162]. Furthermore, the transfer function model used for electricity price forecasting in [163] relates current prices to past prices, errors and demands. However, it should be noted that one should be careful when considering influences factors (e.g. energy demand when forecasting electricity price) other than input data in order not to generate drastic predictions.

Auto Regressive Moving Average (ARMA) model consists of two parts, including Auto Regressive (AR) part and Moving Average (MA) part. The characteristic of the forecast model is determined by the AR parameters, and the way how the forecast model is fitted to the stochastic process dataset is influenced by the MA parameters. The AR and MA part can be applied individually to representing an observed time series. By combining these two parts together, it gives greater flexibility in fitting the time series data.

ARMA model can be mathematically expressed as

$$\emptyset(B)y_t = \theta(B)\varepsilon_t \qquad (II-2)$$

where B is the backward shift operator, $\emptyset(B)$ and $\theta(B)$ is polynomial operators in B [104].

An alternative way to present the ARMA process is

$$y_t = \sum_{j=1}^{p} \emptyset_j y_{t-j} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \qquad (II-3)$$

It can be observed that equation $(II-3)$ is the expansion of equation $(II-2)$. Equation $(II-3)$ has p autoregressive parameters $\emptyset_1$, ..., $\emptyset_p$, and q moving average parameters θ_1,..., θ_q. The term ε_t stands for an uncorrelated normal stochastic process with mean zero and variance σ_ε^2 , and is also uncorrelated with $y_{t-1}, y_{t-2}, \dots , y_{t-p}$

[113]. The stochastic process ε_t normally refers to white noise and an error term, which has random variables with zero mean and constant variance. Therefore, in order to build an ARMA (p, q) model, two parameters should be established, including p autoregressive operators and q moving average operators.

One feature of the ARMA method is the random variables ε_t , which are defined with a constant mean value. Furthermore, the stochastic process for the model is assumed to be stationary and be independent of time t. However, not all the random variables are going to have a constant average value and be stationary all the time. In order to transform a nonstationary stochastic process, one of the common ways that could be applied to the analysis process is simple operators. The simple operators could be i) a nonstationary differencing operator, ii) a logarithm operator, etc. In addition, the two ways of data transformation can be combined to obtain a stationary process. The forecasting process begins with the (transformed) stationary variables no matter in which way the original dataset is dealt with.

Integrated ARMA (ARIMA) models can be employed to fit nonstationary process through differencing the random variables. ARIMA is an extension of ARMA, and it can be generally expressed as

$$\varphi(B)y_t = \left(\emptyset(B)\nabla^d y_t =\right) \theta(B)\varepsilon_t \qquad (II-4)$$

where $\varphi(B) = \emptyset(B)\nabla^d$. $\nabla = (1 - B)$ is a nonstationary operator, and the parameter d shows the differencing degree of the model. The purpose of differencing the data is to achieve a stable dataset with a constant mean. The differencing process can be performed several times within the original data, until a desired stationary dataset with a constant variable is obtained. If d=0, it means there is no differencing degree involved during building the ARIMA model, the stochastic process is stationary and can be present by ARMA time series model.

Another way to transform nonstationary dataset is to apply logarithm to the original stochastic process. The log data transformation is one of the transformation methods proposed as Box-Cox transformation [164]. Example of data processing through log transformation can be found in [113] and [164]. After the log data process, it is essential to check if the logged dataset has a stable mean and variance.

There are also ARIMA models considers seasonality and periodicity, which is called Seasonal ARIMA (SARIMA). SARIMA models are seasonal time series data with similar behaviour in each periodical time intervals. Detailed introduction and formulation of SARIMA time series model could be found in [113].

There are a few applications of ARIMA models in forecasting electricity price, for example, ARIMA is used in [163] and [165] to forecast day-ahead market clearing prices by linking current price to past prices, and current error to past errors. Furthermore, [166] employed SARIMA to predict next day electricity price by adding the feature of periodicity in the forecasting model.

Bibliography

[1]. Ofgem. *Typical Domestic Consumption Values*. 2019 [cited 2019 March 06]; Available from: https://www.ofgem.gov.uk/gas/retail-market/monitoring-data-and-statistics/typical-domestic-consumption-values.

[2]. Qin Zhang and Juan Li. *Demand Response in Electricity Markets: A Review*. in *European Energy Market (EEM), 2012 9th International Conference on the*. 2012. IEEE.

[3]. Nikolaos G Paterakis, Ozan Erdinç, and João PS Catalão, *An Overview of Demand Response: Key-Elements and International Experience.* Renewable and Sustainable Energy Reviews, 2017. **69**: p. 871-891.

[4]. Mohamed H Albadi and EF El-Saadany, *A Summary of Demand Response in Electricity Markets.* Electric Power Systems Research, 2008. **78**(11): p. 1989-1996.

[5]. Chen Chen, Jianhui Wang, and Shalinee Kishore, *A Distributed Direct Load Control Approach for Large-Scale Residential Demand Response.* IEEE Transactions on Power systems, 2014. **29**(5): p. 2219-2228.

[6]. Cuo Zhang, Yan Xu, Zhao Yang Dong, and Jin Ma, *Robust Operation of Microgrids Via Two-Stage Coordinated Energy Storage and Direct Load Control.* IEEE Transactions on Power systems, 2017. **32**(4): p. 2858-2868.

[7]. Kai Heussen, Shi You, Benjamin Biegel, Lars Henrik Hansen, and Katrine B Andersen. *Indirect Control for Demand Side Management-a Conceptual*

Introduction. in *2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*. 2012. IEEE.

[8]. Andrew Ward, *Households Offered First Time-of-Use Energy Tariff*, in *Financial Times*. 02 January 2017: https://www.ft.com/content/ac3b2788-d0eb-11e6-b06b-680c49b4b4c0.

[9]. *Clean Energy for All*. [cited 2019 May]; Available from: https://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union/clean-energy-all-europeans.

[10]. *Clean Energy for All Europeans Communication [Com(2016) 860 Final]* November 2016: https://eur-lex.europa.eu/resource.html?uri=cellar:fa6ea15b-b7b0-11e6-9e3c-01aa75ed71a1.0001.02/DOC_1&format=PDF.

[11]. Energy & Industrial Strategy Department for Business, *Realising the Potential of Demand-Side Response to 2025: A Focus on Small Energy Users (Summary Report)*. November 2017.

[12]. ENA(EnergyNetworkAssociation) *Gb Demand Response Report 1: The Opportunities for Demand Response*. March 10, 2011.

[13]. NG(NationalGrid). *Demand Side Response*. 2017; Available from: http://www2.nationalgrid.com/UK/Services/Balancing-services/Demand-Side-Response/.

[14]. *Hive*. 2019 [cited 2019 May]; Available from: https://www.hivehome.com/.

[15]. Sarvapali D Ramchurn, Perukrishnen Vytelingum, Alex Rogers, and Nick Jennings. *Agent-Based Control for Decentralised Demand Side Management in the Smart Grid*. in *The 10th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*. 2011. International Foundation for Autonomous Agents and Multiagent Systems.

[16]. Valerio Angelucci, Diana Moneta, Renato Urban, and Paolo Gramatica. *Functions and Technologies for Energy Optimization of Users and Districts: Lab Test*. in *2018 AEIT International Annual Conference*. 2018. IEEE.

[17]. Tom Hargreaves, Charlie Wilson, and Richard Hauxwell-Baldwin, *Learning to Live in a Smart Home*. Building Research & Information, 2018. **46**(1): p. 127-139.

[18]. Jamshid Aghaei and Mohammad-Iman Alizadeh, *Multi-Objective Self-Scheduling of Chp (Combined Heat and Power)-Based Microgrids Considering Demand Response Programs and Esss (Energy Storage Systems).* Energy, 2013. **55**: p. 1044-1054.

[19]. Hessam Golmohamadi, Reza Keypour, Birgitte Bak-Jensen, Jayakrishnan Pillai, and Mohammad Hassan Khooban, *Robust Self-Scheduling of Operational Processes for Industrial Demand Response Aggregators.* IEEE Transactions on Industrial Electronics, 2019.

[20]. Mahdi Zarif, Mohammad Hossein Javidi, and Mohammad Sadegh Ghazizadeh, *Self-Scheduling of Large Consumers with Second-Order Stochastic Dominance Constraints.* IEEE Transactions on Power systems, 2013. **28**(1): p. 289-299.

[21]. Sheng Wang, Yi Ding, and Changzheng Shao. *Generalized Modeling of Self-Scheduling Demand Resource in Multi-Energy System*. in *2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*. 2018. IEEE.

[22]. Kunal Patel and Arun Khosla. *Home Energy Management Systems in Future Smart Grid Networks: A Systematic Review.* in *Next Generation Computing Technologies (NGCT), 2015 1st International Conference on*. 2015. IEEE.

[23]. Michael Kaganovich, *Rolling Planning: Optimality and Decentralization.* Journal of Economic Behavior & Organization, 1996. **29**(1): p. 173-185.

[24]. Sereen Althaher, Pierluigi Mancarella, and Joseph Mutale, *Automated Demand Response from Home Energy Management System under Dynamic Pricing and Power and Comfort Constraints.* IEEE Transactions on Smart Grid, 2015. **6**(4): p. 1874-1883.

[25]. Ji Hoon Yoon, Ross Baldick, and Atila Novoselac, *Dynamic Demand Response Controller Based on Real-Time Retail Price for Residential Buildings.* IEEE Transactions on Smart Grid, 2014. **5**(1): p. 121-129.

[26]. S Ali Pourmousavi and M Hashem Nehrir, *Introducing Dynamic Demand Response in the Lfc Model.* IEEE Transactions on Power systems, 2014. **29**(4): p. 1562-1572.

[27]. GR Aghajani, HA Shayanfar, and H Shayeghi, *Demand Side Management in a Smart Micro-Grid in the Presence of Renewable Generation and Demand Response*. Energy, 2017. **126**: p. 622-637.

[28]. Masood Parvania and Mahmud Fotuhi-Firuzabad, *Demand Response Scheduling by Stochastic Scuc*. IEEE Transactions on Smart Grid, 2010. **1**(1): p. 89-98.

[29]. Ofgem, *Ofgem's Decarbonisation Action Plan*. Feb 2020: https://www.ofgem.gov.uk/publications-and-updates/ofgem-s-decarbonisation-action-plan.

[30]. Smartgrid.gov. *What Is the Smart Grid?* 2017 [cited 2017 Jun 27]; Available from: https://www.smartgrid.gov/the_smart_grid/

[31]. Great Britain. Dept. of Energy & Climate Change (DECC) *Smart Grid Vision and Routemap*. 2014.

[32]. Will Spry Liz Waters, *Uk Renewable Electricity Capacity and Generation, April to June 2019*, E.I.S. Department for Business, Editor. 10 October 2019: https://www.gov.uk/government/statistics/energy-trends-section-6-renewables.

[33]. KPMG *Uk Solar Beyond subsidy: The transition*. July 2015.

[34]. Nick Jenkins, Chao Long, and Jianzhong Wu, *An Overview of the Smart Grid in Great Britain*. Engineering, 2015. **1**(4): p. 413-421.

[35]. PowerWise. *Programs & Projects - Demand Side Management*. 2017 [cited 2017 Jun 28]; Available from: http://www.powerwise.gov.ae/en/research/programmes-projects/demand-side-management.html.

[36]. Peter Palensky and Dietmar Dietrich, *Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads*. IEEE transactions on industrial informatics, 2011. **7**(3): p. 381-388.

[37]. Nur Mohammad and Yateendra Mishra, *Demand-Side Management and Demand Response for Smart Grid*, in *Smart Grids and Their Communication Systems*. 2019, Springer. p. 197-231.

[38]. N. Zhang, L.F. Ochoa, and D.S. Kirschen. *Investigating the Impact of Demand Side Management on Residential Customers*. in *2011 2nd IEEE PES*

International Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe), . 2011. IEEE.

[39]. T Adefarati and RC Bansal, *Energizing Renewable Energy Systems and Distribution Generation*, in *Pathways to a Smarter Power System*. 2019, Elsevier. p. 29-65.

[40]. Goran Strbac, *Demand Side Management: Benefits and Challenges.* Energy Policy, 2008. **36**(12): p. 4419-4426.

[41]. Energy & Industrial Strategy (BEIS) Great Britain. Dept. for Business *Energy Trends: December 2016, Special Feature Article - Electricity Generation and Supply Figures for Scotland, Wales, Northern Ireland and England, 2012 to 2015*. 22 December 2016.

[42]. Italo Atzeni, Luis G Ordóñez, Gesualdo Scutari, Daniel P Palomar, and Javier Rodríguez Fonollosa, *Demand-Side Management Via Distributed Energy Generation and Storage Optimization.* IEEE Transactions on Smart Grid, 2013. **4**(2): p. 866-876.

[43]. Jacopo Torriti, Mohamed G Hassan, and Matthew Leach, *Demand Response Experience in Europe: Policies, Programmes and Implementation.* Energy, 2010. **35**(4): p. 1575-1583.

[44]. Ozan Erdinc, Akın Taşcikaraoğlu, Nikolaos G Paterakis, and João PS Catalão, *Novel Incentive Mechanism for End-Users Enrolled in Dlc-Based Demand Response Programs within Stochastic Planning Context.* IEEE Transactions on Industrial Electronics, 2019. **66**(2): p. 1476-1487.

[45]. Kun-Yuan Huang and Yann-Chang Huang, *Integrating Direct Load Control with Interruptible Load Management to Provide Instantaneous Reserves for Ancillary Services.* IEEE Transactions on Power systems, 2004. **19**(3): p. 1626-1634.

[46]. K Bhattacharya, *Competitive Framework for Procurement of Interruptible Load Services.* IEEE Transactions on Power systems, 2003. **18**(2): p. 889-897.

[47]. Ning Lu, *An Evaluation of the Hvac Load Potential for Providing Load Balancing Service.* IEEE Transactions on Smart Grid, 2012. **3**(3): p. 1263-1270.

[48]. Greenage. *Time of Use Tariff*. 2017 [cited 2017 Jun 28]; Available from: https://www.thegreenage.co.uk/time-of-use-tariff-smart-grid/.

[49]. Smartgrid.gov. *Time Based Rate Programs*. 2017 [cited 2017 Jun 28]; Available from: https://www.smartgrid.gov/recovery_act/time_based_rate_programs.html.

[50]. Emre Celebi and J David Fuller, *Time-of-Use Pricing in Electricity Markets under Different Market Structures*. IEEE Transactions on Power systems, 2012. **27**(3): p. 1170-1181.

[51]. Jacopo Torriti, *Price-Based Demand Side Management: Assessing the Impacts of Time-of-Use Tariffs on Residential Electricity Demand and Peak Shifting in Northern Italy*. Energy, 2012. **44**(1): p. 576-583.

[52]. Matthias Altmann, P Schmidt, H Landinger, J Michalski, A Brenninkmeijer, I Buscke, et al., *Effect of Smart Metering on Electricity Prices*. Study for the European Parliament, 2011. **130**.

[53]. Matteo Muratori and Giorgio Rizzoni, *Residential Demand Response: Dynamic Energy Management and Time-Varying Electricity Pricing*. IEEE Transactions on Power systems, 2015. **31**(2): p. 1108-1117.

[54]. S Ali Pourmousavi, Stasha N Patrick, and M Hashem Nehrir, *Real-Time Demand Response through Aggregate Electric Water Heaters for Load Shifting and Balancing Wind Generation*. IEEE Transactions on Smart Grid, 2014. **5**(2): p. 769-778.

[55]. OVOEnergy. *Economy 7*. 2019 [cited 2019 March 04]; Available from: https://www.ovoenergy.com/guides/energy-guides/economy-7.html.

[56]. Karen Herter, Patrick McAuliffe, and Arthur Rosenfeld, *An Exploratory Analysis of California Residential Customer Response to Critical Peak Pricing of Electricity*. Energy, 2007. **32**(1): p. 25-34.

[57]. Karen Herter and Seth Wayland, *Residential Response to Critical-Peak Pricing of Electricity: California Evidence*. Energy, 2010. **35**(4): p. 1561-1567.

[58]. Juan M Lujano-Rojas, Cláudio Monteiro, Rodolfo Dufo-López, and José L Bernal-Agustín, *Optimum Residential Load Management Strategy for Real Time Pricing (Rtp) Demand Response Programs*. Energy Policy, 2012. **45**: p. 671-679.

[59]. Antonio J Conejo, Juan M Morales, and Luis Baringo, *Real-Time Demand Response Model*. IEEE Transactions on Smart Grid, 2010. **1**(3): p. 236-242.

[60]. Cynthujah Vivekananthan, Yateendra Mishra, and Fangxing Li, *Real-Time Price Based Home Energy Management Scheduler*. IEEE Transactions on Power systems, 2015. **30**(4): p. 2149-2159.

[61]. Andrew J Roscoe and G Ault, *Supporting High Penetrations of Renewable Generation Via Implementation of Real-Time Electricity Pricing and Demand Response*. IET renewable power generation, 2010. **4**(4): p. 369-382.

[62]. Gov.uk. *Smart Meters: A Guide*. 2017 [cited 2017 Jun 28]; Available from: https://www.gov.uk/guidance/smart-meters-how-they-work.

[63]. Great Britain. Dept. of Energy & Climate Change (DECC) *Smart Metering Implementation Programme*.

[64]. European Commission. *Clean Energy for All Europeans*. 2019 [cited 2019 May]; Available from: https://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union/clean-energy-all-europeans.

[65]. Mubbashir Ali, Juha Jokisalo, Kai Siren, Amir Safdarian, and Matti Lehtonen, *A User-Centric Demand Response Framework for Residential Heating, Ventilation, and Air-Conditioning Load Management*. Electric Power Components and Systems, 2016. **44**(1): p. 99-109.

[66]. Yu-Hsiu Lin and Yu-Chen Hu, *Residential Consumer-Centric Demand-Side Management Based on Energy Disaggregation-Piloting Constrained Swarm Intelligence: Towards Edge Computing*. Sensors, 2018. **18**(5): p. 1365.

[67]. Abdallah M Elsayed, Mohamed M Hegab, and Sobhy M Farrag, *Smart Residential Load Management Technique for Distribution Systems' Performance Enhancement and Consumers' Satisfaction Achievement*. International Transactions on Electrical Energy Systems, 2019: p. e2795.

[68]. Hamed Mohsenian-Rad, *Optimal Demand Bidding for Time-Shiftable Loads*. IEEE Transactions on Power systems, 2014. **30**(2): p. 939-951.

[69]. Yi-Chang Li and Seung Ho Hong, *Real-Time Demand Bidding for Energy Management in Discrete Manufacturing Facilities*. IEEE Transactions on Industrial Electronics, 2016. **64**(1): p. 739-749.

[70]. NG(NationalGrid) *Power Responsive Dsr Product Map Glossary*. December 2015.

[71]. Karen Stenner, Elisha R Frederiks, Elizabeth V Hobman, and Stephanie Cook, *Willingness to Participate in Direct Load Control: The Role of Consumer Distrust.* Applied energy, 2017. **189**: p. 76-88.

[72]. Costas Efthymiou and Georgios Kalogridis. *Smart Grid Privacy Via Anonymization of Smart Metering Data*. in *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*. 2010. IEEE.

[73]. BEIS, *Smart Meters: Quarterly Report to End June 2018.* 30 August 2018.

[74]. uSwitch. *Smart Meters Explained*. 2017 [cited 2017 July 03]; Available from: https://www.uswitch.com/gas-electricity/guides/smart-meters-explained/.

[75]. DJ Hammerstrom, R Ambrosio, J Brous, TA Carlon, DP Chassin, JG DeSteese, et al., *Pacific Northwest Gridwise Testbed Demonstration Projects.* Part I. Olympic Peninsula Project, 2007. **210**.

[76]. Anthony Star, Anne Evens, Marjorie Isaacson, Larry Kotewa, and CNT Energy. *Making Waves in the Heartland: How Illinois' Experience with Residential Real-Time Pricing Can Be a National Model*. in *Proceedings*. 2008.

[77]. ADDRESS. *Towards the Smart Grids of the Future*. 2017 [cited 2017 July 06]; Available from: http://www.addressfp7.org/index.html.

[78]. CORDIS - EU research results. *Simulation Supported Real Time Energy Management in Building Blocks*. July 2019 [cited 2019 October 30]; Available from: https://cordis.europa.eu/project/rcn/200154/factsheet/en.

[79]. Sim4Block. *Sim4block*. 2019 [cited 2019 October 30]; Available from: https://www.sim4blocks.eu/#.

[80]. CORDIS - EU Research Results. *Edream - Enabling New Demand Response Advanced, Market Oriented and Secure Technologies, Solutions and Business Models*. January 2018 [cited 2019 October 30]; Available from: https://cordis.europa.eu/project/rcn/212892/factsheet/en.

[81]. eDREAM. *Edream - Enabling New Demand Response Advanced, Market Oriented and Secure Technologies, Solutions and Business Models*. 2019 [cited 2019 October 30]; Available from: https://edream-h2020.eu/.

[82]. SSEN (Scottish and Southern Electricity Network). *Nines Supporting Shetland's Sustainable Future*. 2017 Jun 16 [cited 2017 July 06]; Available from: http://www.ninessmartgrid.co.uk/#.

[83]. SSE Networks. *Solent Achieving Value from Efficiency*. [cited 2019 October 31]; Available from: https://save-project.co.uk/.

[84]. UK Power Networks. *Energywise*. 2019 [cited 2019 October 31; Available from: https://innovation.ukpowernetworks.co.uk/projects/energywise/.

[85]. Western Power Distribution. *Project Entire*. 2019 [cited 2019 October 31]; Available from: https://www.westernpower.co.uk/innovation/projects/project-entire.

[86]. Western Power Distribution. *What Is Falcon?* 2019 [cited 2019 October 31]; Available from: https://www.westernpower.co.uk/innovation/projects/falcon.

[87]. Han Xu and Ivana Kockar. *Participation of Customers in Active Demand Side Participation Programs under Different Pricing Schemes*. in *2016 IEEE Power and Energy Society General Meeting (PESGM)*. 2016. IEEE.

[88]. Ofgem. *Transition to Smart Meters*. 2017 [cited 2017 Jun 30]; Available from: https://www.ofgem.gov.uk/gas/retail-market/metering/transition-smart-meters.

[89]. Vera Silva, Vladimir Stanojevic, Marko Aunedi, Danny Pudjianto, and Goran Strbac, *Smart Domestic Appliances as Enabling Technology for Demand-Side Integration: Modelling, Value and Drivers.* The Future of Electricity Demand: Customers, Citizens and Loads, 2011. **2011**: p. 185-211.

[90]. Laura M Platchkov and Michael G Pollitt, *The Economics of Energy (and Electricity) Demand.* The Future of Electricity Demand: Customers, Citizens and Loads, 2011. **69**: p. 17.

[91]. Jun Hong, Cameron M Johnstone, Jae Min Kim, and Paul Tuohy, *5 Demand-Side Management and Control in Buildings.* The Future of Electricity Demand: Customers, Citizens and Loads, 2011. **69**: p. 129.

[92]. Laura M Platchkov, Michael G Pollitt, David Reiner, and Irina Shaorshadze, *2010 Eprg Public Opinion Survey: Policy Preferences and Energy Saving Measures.* 2011.

[93]. Laurence A Wolsey and George L Nemhauser, *Integer and Combinatorial Optimization*. Vol. 55. 1999: John Wiley & Sons.

[94]. FICO. *Fico® Xpress Optimization Suite*. 2017 [cited 2017 July 25]; Available from: http://www.fico.com/en/products/fico-xpress-optimization-suite.

[95]. Great Britain. Dept. of Energy & Climate Change (DECC), *Solar Pv Strategy Part 1: Roadmap to a Brighter Future.* URN 13D/251 Department of Energy & Climate Change (Oct. 2013) https://www. gov. uk/government/publications/uk-solar-pv-strategy-part-1-roadmap-to-a-brighter-future, 2013.

[96]. Ian Richardson, Murray Thomson, David Infield, and Conor Clifford, *Domestic Electricity Use: A High-Resolution Energy Demand Model.* Energy and buildings, 2010. **42**(10): p. 1878-1887.

[97]. Ian Richardson and Murray Thomson, *Domestic Electricity Demand Model-Simulation Example.* 2010.

[98]. Changsong Chen, Shanxu Duan, Tong Cai, Bangyin Liu, and Gangwei Hu, *Smart Energy Management System for Optimal Microgrid Economic Operation.* IET renewable power generation, 2011. **5**(3): p. 258-267.

[99]. Nissan. *Nissan Leaf - Ranges & Charging*. 2019 [cited 25 April 2019] Available from: https://www.nissan.co.uk/vehicles/new-vehicles/leaf/range-charging.html.

[100]. Dimplex. *Xle Storage Heater*. 20 October 2017 [cited 2019 May]; Available from: https://www.tlc-direct.co.uk/Technical/DataSheets/Dimplex1/DXXLE_Datasheet.pdf.

[101]. Ofgem. *Feed-in Tariff (Fit) Rates*. 2017 [cited 2017 July 28]; Available from: https://www.ofgem.gov.uk/environmental-programmes/fit/fit-tariff-rates.

[102]. Sanjeev Kumar Aggarwal, Lalit Mohan Saini, and Ashwani Kumar, *Electricity Price Forecasting in Deregulated Markets: A Review and Evaluation.* International Journal of Electrical Power & Energy Systems, 2009. **31**(1): p. 13-22.

[103]. Rafał Weron, *Electricity Price Forecasting: A Review of the State-of-the-Art with a Look into the Future.* International Journal of Forecasting, 2014. **30**(4): p. 1030-1081.

[104]. George E. P. Box, *Time Series Analysis Forecasting and Control*, ed. M.J. Gwilym, C.R. Gregory, and P.D.A. Dawsonera. 2008: Oxford : Wiley.

[105]. PJM. *Energy Market*. 2017 [cited 2017 19 October]; Available from: http://www.pjm.com/markets-and-operations/energy.aspx.

[106]. Lucien Le Cam, *Maximum Likelihood: An Introduction.* International Statistical Review/Revue Internationale de Statistique, 1990: p. 153-171.

[107]. In Jae Myung, *Tutorial on Maximum Likelihood Estimation.* Journal of mathematical Psychology, 2003. **47**(1): p. 90-100.

[108]. Mathworks®, *Matlab 2017a*. 2017.

[109]. George EP Box and David A Pierce, *Distribution of Residual Autocorrelations in Autoregressive-Integrated Moving Average Time Series Models.* Journal of the American statistical Association, 1970. **65**(332): p. 1509-1526.

[110]. Hirotugu Akaike, *A New Look at the Statistical Model Identification.* IEEE transactions on automatic control, 1974. **19**(6): p. 716-723.

[111]. Gideon Schwarz, *Estimating the Dimension of a Model.* The annals of statistics, 1978. **6**(2): p. 461-464.

[112]. DG Mayer and DG Butler, *Statistical Validation.* Ecological modelling, 1993. **68**(1-2): p. 21-32.

[113]. Antonio J Conejo, Miguel Carrión, and Juan M Morales, *Decision Making under Uncertainty in Electricity Markets*. Vol. 153. 2010: Springer.

[114]. Peter Kall, Stein W Wallace, and Peter Kall, *Stochastic Programming*. 1994: Springer.

[115]. Holger Heitsch and Werner Römisch, *Scenario Reduction Algorithms in Stochastic Programming.* Computational optimization and applications, 2003. **24**(2-3): p. 187-206.

[116]. Nicole Growe-Kuska, Holger Heitsch, and Werner Romisch. *Scenario Reduction and Scenario Tree Construction for Power Management Problems*. in *Power tech conference proceedings, 2003 IEEE Bologna*. 2003. IEEE.

[117]. Jitka Dupačová, N. Groewe-Kuska, and Werner Roemisch, *Scenario Reduction in Stochastic Programming: An Approach Using Probability Metrics*. Vol. 95. 2003. 493.

[118]. David Arthur and Sergei Vassilvitskii. *K-Means++: The Advantages of Careful Seeding*. in *Proceedings of the eighteenth annual ACM-SIAM symposium on Discrete algorithms*. 2007. Society for Industrial and Applied Mathematics.

[119]. Kristina Šutienė, Dalius Makackas, and Henrikas Pranevičius, *Multistage K-Means Clustering for Scenario Tree Construction.* Informatica, 2010. **21**(1): p. 123-138.

[120]. Patrizia Beraldi and Maria Elena Bruni, *A Clustering Approach for Scenario Tree Reduction: An Application to a Stochastic Programming Portfolio Optimization Problem.* Top, 2014. **22**(3): p. 934-949.

[121]. James E Smith, *Moment Methods for Decision Analysis.* Management science, 1993. **39**(3): p. 340-358.

[122]. Kjetil Høyland, Michal Kaut, and Stein W Wallace, *A Heuristic for Moment-Matching Scenario Generation.* Computational optimization and applications, 2003. **24**(2): p. 169-185.

[123]. Michal Kaut and Stein W Wallace, *Evaluation of Scenario-Generation Methods for Stochastic Programming.* 2003.

[124]. Alexander Shapiro, *Monte Carlo Sampling Methods.* Handbooks in operations research and management science, 2003. **10**: p. 353-425.

[125]. Radford M Neal, *Annealed Importance Sampling.* Statistics and computing, 2001. **11**(2): p. 125-139.

[126]. Werner Römisch. *Scenario Reduction Techniques in Stochastic Programming*. in *SAGA*. 2009. Springer.

[127]. Juan M Morales, Salvador Pineda, Antonio J Conejo, and Miguel Carrion, *Scenario Reduction for Futures Market Trading in Electricity Markets.* IEEE Transactions on Power systems, 2009. **24**(2): p. 878-888.

[128]. Holger Heitsch and Werner Römisch, *Scenario Tree Modeling for Multistage Stochastic Programs.* Mathematical programming, 2009. **118**(2): p. 371-406.

[129]. Stuart Lloyd, *Least Squares Quantization in Pcm.* IEEE transactions on information theory, 1982. **28**(2): p. 129-137.

[130]. Peter J Rousseeuw, *Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis.* Journal of computational and applied mathematics, 1987. **20**: p. 53-65.

[131]. V Sridharan, William L Berry, and V Udayabhanu, *Freezing the Master Production Schedule under Rolling Planning Horizons.* Management science, 1987. **33**(9): p. 1137-1149.

[132]. Sri V Sridharan, William L Berry, and V Udayabhanu, *Measuring Master Production Schedule Stability under Rolling Planning Horizons.* Decision Sciences, 1988. **19**(1): p. 147-166.

[133]. Raik Stolletz and Emilio Zamorano, *A Rolling Planning Horizon Heuristic for Scheduling Agents with Different Qualifications.* Transportation Research Part E: Logistics and Transportation Review, 2014. **68**: p. 39-52.

[134]. Aidan Tuohy, Peter Meibom, Eleanor Denny, and Mark O'Malley, *Unit Commitment for Systems with Significant Wind Penetration.* IEEE Transactions on Power systems, 2009. **24**(2): p. 592-601.

[135]. Alf Kimms, *Rolling Planning Horizon*, in *Multi-Level Lot Sizing and Scheduling*. 1997, Springer. p. 239-245.

[136]. Ofgem. *Retail Energy Markets in 2016*. 3rd August 2016 [cited 2019 March 06]; Available from: https://www.ofgem.gov.uk/publications-and-updates/retail-energy-markets-2016.

[137]. Shengnan Shao, Manisa Pipattanasomporn, and Saifur Rahman, *Development of Physical-Based Demand Response-Enabled Residential Load Models.* IEEE Transactions on Power systems, 2013. **28**(2): p. 607-614.

[138]. Manisa Pipattanasomporn, Murat Kuzlu, and Saifur Rahman, *An Algorithm for Intelligent Home Energy Management and Demand Response Analysis.* IEEE Transactions on Smart Grid, 2012. **3**(4): p. 2166-2173.

[139]. PA Consulting Group; Ofgem, *Aggregators - Barriers and External Impacts*. May 2016: Available from: https://www.ofgem.gov.uk/system/files/docs/2016/07/aggregators_barriers_and_external_impacts_a_report_by_pa_consulting_0.pdf.

[140]. PS Dolan, MH Nehrir, and V Gerez, *Development of a Monte Carlo Based Aggregate Model for Residential Electric Water Heater Loads.* Electric Power Systems Research, 1996. **36**(1): p. 29-35.

[141]. Cristian Perfumo, Ernesto Kofman, Julio H Braslavsky, and John K Ward, *Load Management: Model-Based Control of Aggregate Power for Populations of Thermostatically Controlled Loads.* Energy Conversion and Management, 2012. **55**: p. 36-48.

[142]. Wei Zhang, Karanjit Kalsi, Jason Fuller, Marcelo Elizondo, and David Chassin. *Aggregate Model for Heterogeneous Thermostatically Controlled Loads with Demand Response*. in *2012 IEEE Power and Energy Society General Meeting*. 2012. IEEE.

[143]. James A Hendler, Austin Tate, and Mark Drummond, *Ai Planning: Systems and Techniques.* AI magazine, 1990. **11**(2): p. 61-61.

[144]. Pacific Northwest National Laboratory. *Bringing Power to the People*. 2019 [cited 2019 March 07]; Available from: http://eioc.pnnl.gov/research/gridwise.stm.

[145]. Regine Belhomme, Ramon Cerero, Giovanni Valtorta, and Philippe Eyrolles. *The Address Project: Developing Active Demand in Smart Power Systems Integrating Renewables*. in *Power and Energy Society General Meeting, 2011 IEEE*. 2011. IEEE.

[146]. Grid Innovation Online. *Address Project: Demonstration in France*. 2017 [cited 2017 July 06]; Available from: http://grid.imginternet.it/Articles/Library/Demonstration-In-France-ADDRESS-PROJECT.kl.

[147]. ADDRESS *Adress- Active Demand*. May 2013.

[148]. Sarah Mander; Dana Abi Ghanem *D5.2 Key Societal Factors Influencing the Adoption of the Address Smart Grids Architecture*. May 31st, 2013.

[149]. Alessandro Agnetis, Gabriella Dellino, Paolo Detti, Giacomo Innocenti, Gianluca de Pascale, and Antonio Vicino. *Appliance Operation Scheduling for Electricity Consumption Optimization*. in *Decision and Control and European Control Conference (CDC-ECC), 2011 50th IEEE Conference on*. 2011. IEEE.

[150]. Alessandro Agnetis, Gianluca de Pascale, Paolo Detti, and Antonio Vicino, *Load Scheduling for Household Energy Consumption Optimization.* IEEE Transactions on Smart Grid, 2013. **4**(4): p. 2364-2373.

[151]. Stevie Adams; Alex Howison; Stewart Reid, *Nines Project Closedown Report*. April 2017: http://www.ninessmartgrid.co.uk/wp-content/uploads/2017/05/SSEN-NINES-Project-CloseDown-Report_designed2.pdf.

[152]. Smarter Grid Solutions. 2018; Available from: https://www.smartergridsolutions.com/.

[153]. Han Xu; Grant Allan; Fulin Fan; Ivana Kockar *6a - Nines Commercial Arrangements and Economics Report*. 2017.

[154]. Raheal McGhee Joe Clarke, Kati Svehla *Nines Project 1b Dsm Infrastructure Report* 2017.

[155]. Andrew Cowie Joe Clarke, Kati Svehla *Nines Project 1c Dsm Network Benefits Report* 2017.

[156]. BR Szkuta, L Augusto Sanabria, and Tharam S Dillon, *Electricity Price Short-Term Forecasting Using Artificial Neural Networks.* IEEE Transactions on Power systems, 1999. **14**(3): p. 851-857.

[157]. Y-Y Hong and C-Y Hsiao, *Locational Marginal Price Forecasting in Deregulated Electricity Markets Using Artificial Intelligence.* IEE Proceedings-Generation, Transmission and Distribution, 2002. **149**(5): p. 621-626.

[158]. S Anbazhagan and Narayanan Kumarappan, *Day-Ahead Deregulated Electricity Market Price Forecasting Using Recurrent Neural Network.* IEEE Systems Journal, 2013. **7**(4): p. 866-872.

[159]. HY Yamin, SM Shahidehpour, and Z Li, *Adaptive Short-Term Electricity Price Forecasting Using Artificial Neural Networks in the Restructured Power Markets.* International Journal of Electrical Power & Energy Systems, 2004. **26**(8): p. 571-581.

[160]. Paras Mandal, Tomonobu Senjyu, Naomitsu Urasaki, Toshihisa Funabashi, and Anurag K Srivastava, *A Novel Approach to Forecast Electricity Price for Pjm Using Neural Network and Similar Days Method.* IEEE Transactions on Power systems, 2007. **22**(4): p. 2058-2065.

[161]. Deepak Singhal and KS Swarup, *Electricity Price Forecasting Using Artificial Neural Networks.* International Journal of Electrical Power & Energy Systems, 2011. **33**(3): p. 550-555.

[162]. FJ Nogales and Antonio J Conejo, *Electricity Price Forecasting through Transfer Function Models.* Journal of the Operational Research Society, 2006. **57**(4): p. 350-356.

[163]. Antonio J. Conejo, Javier Contreras, Rosa Espínola, and Miguel A. Plazas, *Forecasting Electricity Prices for a Day-Ahead Pool-Based Electric Energy Market.* International Journal of Forecasting, 2005. **21**(3): p. 435-462.

[164]. George EP Box and David R Cox, *An Analysis of Transformations.* Journal of the Royal Statistical Society. Series B (Methodological), 1964: p. 211-252.

[165]. T Jakasa, I Androcec, and P Sprcic. *Electricity Price Forecasting—Arima Model Approach*. in *Energy Market (EEM), 2011 8th International Conference on the European*. 2011. IEEE.

[166]. Javier Contreras, Rosario Espinola, Francisco J Nogales, and Antonio J Conejo, *Arima Models to Predict Next-Day Electricity Prices.* Power Systems, IEEE Transactions on, 2003. **18**(3): p. 1014-1020.