

Regulated Generation Allocation and Operation
Optimisation for Networks with New Variable Independent
Power Production and Self-Generation

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Abstract

The world is moving towards legally binding targets for decarbonisation, with considerable interest in cost effective energy pathways that will have positive socio-economic, environmental and health impacts. The electricity sector is progressing by adopting renewable energy as a replacement for fossil fuel-based electricity generation. As renewable energy sources (RES) in the form of independent power production (IPP) and on-site or self-generation (SG) proliferate on power networks, questions arise about their impact on the financial integrity of the traditional power distribution business. As distribution companies (DISCOs) act to protect their own financial interests, network access barriers will be presented to emerging RES. Network regulation is expected to drive DISCOs to pursue a more socially desirable outcome. However, today's methods of network regulation are not adequate enough to remove the barriers and still ensure renewable energy goals are met. In fact there are no widely-accepted and clear mechanisms to encourage DISCOs to coordinate distributed generation, let alone SG and IPP, integration in a cost-effective manner. In terms of policy, companies can be obligated to meet a quota of RES in their energy supply. But this obligation is usually not guaranteed to align with the capabilities of power networks, which typically suffer from voltage and congestion constraints among others. To set achievable quotas there is a need for a more adaptable mechanism that takes into account capacity constraints.

The work of this thesis concerns the formulation and empirical analyses of optimisation models of structured RES allocation by a regulated DISCO, and the regulating authority's role in influencing the DISCO's planning approach and promoting socially desirable performance. The developed optimisation models uniquely: introduce combined SG and IPP allocation, which allows generation to be defined in association with

on-site demand; provide generation capacity that simultaneously meets network, policy and regulatory requirements (i.e. there is no need to individually evaluate the same implications from the calculated capacity); take account of generation curtailment and its underlying restrictions for SG and IPP; demonstrate SG and IPP allocations for range of quota obligations; and benchmark the performance of the models against alternative approaches of generation allocation and regulation.

This results in a problem with a multilevel structure necessitating the computation of spatial capacity and a solution to the multi-period optimal power flow. The problem variables further depend on the perspective of stakeholders in the electricity market. From the viewpoint of the DISCO, the solution intends to provide suitably sited DG capacity and maximise profit. As for the regulating authority the results offer the most suitable reward or penalty to drive the DISCO towards a low carbon network. In response, the regulated DISCO should then carry out DG planning in line with broader goals of society. This joint SG and IPP integration problem lends itself specific and unique constraints including generation class-specific net generation and energy curtailment.

The results reported in this thesis highlight the value and performance of the DISCO and regulation optimisation models on several power networks of varying size and composition. Numerical experiments demonstrate the developed DISCO optimisation model outperforms standard models, concerned primarily with capacity maximisation, in satisfying the following binding constraints: minimum IPP capacity and SG net energy. It is further revealed that integrating SG and IPP in a benchmark system with the proposed model increases profit by up to 23.7%, adding an improvement of 8% over a feasible standard model. In a case study of a network with extremely limited capacity—insufficient for minimum IPP—it is shown using the regulation optimisation model that to maintain the required DISCO profit the incentives can range from 2% to 14% of revenue for quota obligations spanning 10% to 50% of network load. The regulation optimisation model is compared with decoupling, a familiar method for removing energy retail impacts on revenue. Results show that regulation optimisation model is able to maintain a steadier profit with increasing quota requirements.

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Abbreviations

| | |
|-------|--------------------------------|
| ACP | Alternative Compliance Payment |
| ANC | Approximate Network Capacity |
| ANM | Active Network Management |
| DG | Distributed Generation |
| DISCO | Distribution Company |
| DNO | Distribution Network Operator |
| DSM | Demand-Side Management |
| DSO | Distribution System Operator |
| EE | Energy Efficiency |
| FiT | Feed-in Tariff |
| GENCO | Generation Company |
| IPM | Interior-Point Method |
| IPP | Independent Power Production |
| NLP | Nonlinear Programming |
| OLTC | On-load Tap Changer |
| OPF | Optimal Power Flow |
| PPA | Power Purchase Contract |
| PSO | Particle Swarm Optimisation |
| PV | Photovoltaic |
| RA | Regulating Authority |
| REC | Renewable Energy Certificate |
| RES | Renewable Energy sources |

Contents

| | |
|--------|---|
| RPF | Reverse Power Flow |
| RPM | Reward/Penalty Mechanism |
| RPS | Renewable Portfolio Standard |
| RSILCO | Regulated SG and IPP Location and Capacity Optimisation |
| SILCO | SG and IPP Location and Capacity Optimisation |
| SG | Self-Generation |

Nomenclature

Sets and Indices

| | |
|-----|--|
| D | Set consisting of all buses in the system. |
| i | Candidate IPP bus index. |
| I | Set consisting of all candidate IPP buses in the system. |
| k | Candidate SG bus index. |
| K | Set consisting of all candidate SG buses in the system. |
| t | Time interval index, in hourly steps. |
| N | Set consisting of all time segments over a year. |

Parameters

| | |
|--------------|---|
| C^e | Wholesale price of electricity (£/MWh). |
| C^r | Retail price of electricity (£/MWh). |
| C^b | Penalty rate for obligation non-compliance (£/MWh). |
| C^{rv} | Revenue recovery rate (£/MWh). |
| C^{ee} | DISCO energy export rate (£/MWh). |
| a_F | Budget or financial resource to support RES integration (£). |
| r^o | Independent power production quota to be met by DISCO (%). |
| r^s | Target for self-generation (%). |
| a_L | Allowed total energy generation for SG (%). |
| G_k^{\min} | Minimum allowable capacity for SG (MW). |
| G_k^{\max} | Maximum allowable capacity for SG (MW). |
| G_i^{\max} | Maximum allowable capacity for independent power production (MW). |
| G_i^{\max} | Minimum allowable capacity for independent power production (MW). |

Contents

| | |
|-----------------------|---|
| $\tilde{P}_{SG,k}^t$ | SG time series scale factor. |
| $\tilde{P}_{IPP,i}^t$ | IPP time series scale factor. |
| α_{SG}^{\max} | Maximum allowable curtailment of SG (pu). |
| α_{IPP}^{\max} | Maximum allowable curtailment of IPP (pu). |
| $P_{EXP,k}^{\min}$ | Minimum exported power for SG (MW). |
| $P_{EXP,k}^{\max}$ | Maximum exported power for SG (MW). |
| a_{ESk} | Energy curtailment limit for SG (pu). |
| a_{EIi} | Energy curtailment limit for IPP (pu). |
| $S_{d,j}^{\max}$ | Apparent power limit of component between bus d and bus j . |
| G_{dj}^t | Real part of admittance element between bus d and bus j (S). |
| B_{dj}^t | Imaginary part of admittance element between bus d and bus j (S). |

Variables

| | |
|--------------------|---|
| $G_{IPP,i}$ | Generation capacity of the i -th IPP. |
| u_i | Connection status for i -th IPP. |
| $G_{SG,k}$ | Generation capacity of the k -th SG. |
| C^b | Penalty rate for obligation non-compliance (Chapters 5 & 6) (£/MWh). |
| C^{rv} | Revenue recovery rate (Chapters 5 & 6) (£/MWh). |
| C^{ee} | DISCO energy export rate (Chapters 5 & 6) (£/MWh). |
| $P_{IPP,i}^t$ | Independent power production at i -th candidate bus and t -th time interval (MW). |
| $P_{SG,k}^t$ | Self-generation at k -th candidate bus and t -th time interval (MW). |
| $P_{L,a}^t$ | Active power demand associated with i -th SG and t -th time interval (MW). |
| $\alpha_{SG,k}^t$ | Active power curtailment of i -th SG and t -th time interval (pu). |
| $\alpha_{IPP,i}^t$ | Active power curtailment of k -th SG and t -th time interval (pu). |
| P_s^t | Total power delivered from substation (MW). |
| $P_{L,d}^t$ | Active power demand at d th bus and t th time interval (pu). |
| $Q_{L,d}^t$ | Reactive power demand at d th bus and t th time interval (pu). |
| u_c | Status of DISCO compliance with reference to obligation level. |
| $P_{G,d}^t$ | Active power supply at d th bus and t th time interval (pu). |
| $Q_{G,d}^t$ | Reactive power supply at d th bus and t th time interval (pu). |

Contents

- P_s^t Active power supply required by the distribution system.
- V_d^t, V_j^t Bus voltages magnitude at t th time interval (pu).
- δ_d^t, δ_j^t Bus voltage angles at t th time interval.

The following sign function is defined to simplify the expression of connection and compliance statuses:

$$\text{sgn}^+(x) = \begin{cases} 1, & \text{if } x > 0; \\ 0, & \text{if } x \leq 0. \end{cases} \quad (1)$$

Chapter 1

Introduction

1.1 Research Rationale and Motivation

Fossil fuel-based electricity generation is responsible for a significant amount of air pollutants and greenhouse gas emissions, which pose severe public health risk and contribute to anthropogenic climate change [1, 2].

The imperative to implement measures to slow down climate change has resonated with policymakers globally. In 2015, 195 countries committed to the Paris Agreement at the 21st Conference of Parties. The agreement states that the signatories will aim to keep the increase in global average temperature to “well below 2°C and to pursue efforts to limit the temperature increase to 1.5°C above pre-industrial levels” [3].

Yet the world’s mitigation plans for the period 2020 to 2030 fall short of satisfying the requirements for realising the temperature goal [1]. The 2018 IPCC special report revealed that more ambitious pathways are necessary [4]. Most of these pathways include a major role for renewable energy sources (RES) [5–7].

At least 164 countries have had some form of target setting for renewable energy, as of 2015. Furthermore, the targets in 59 jurisdictions are legally binding [8]. Further progress requires policymakers to send even clearer signals about the need to replace fossil fuel-based electricity generation with RES at accelerated rates. Developed countries will need to take the lead by retiring coal-fired power plants early—by 2030 in OECD countries according to [9]. Some regions have promptly embraced the clean

energy future, setting more aggressive goals such as achieving 100% renewable energy and zero-carbon supply by 2045 [10].

In the midst of these plans are ongoing debates over the most cost-effective pathways towards low carbon energy systems [5,6,11,12]. Even when narrowed to electricity delivery and retail, the challenges are just as formidable [6]. Although there is considerable work on the costs and benefits of DG integration within power networks [13–16], important questions remain, like how to cost-effectively transition to low carbon networks in more realistic conditions i.e., to overcome the combined financial effects of network constraints [17], regulation [18] and RES policy [19–21].

Such an efficient transition to low carbon networks raises several important cost concerns, which motivate the work of this thesis. First, a large amount of RES is integrated as distributed generation (DG) in distribution (including sub-transmission) networks owned and operated by distribution network operators (DNOs) or distribution companies (DISCOs)¹. The capacity of these networks to connect RES is constrained by numerous requirements, including the need for safe and reliable network operation. These requirements are enforced by regulating authorities (RAs), which also oversee in different ways the remuneration of DISCOs. Once network capacity is exhausted and there exist further RES connection requests, DISCOs mostly reinforce their networks by upgrading or adding new network elements. This constitutes a major cost component that will likely be claimed in some form from RES developers [22].

Second, to encourage RES investment, policymakers typically institute renewable energy programmes with obligations or mandates for DISCOs and financial support mechanisms for qualifying technologies [8, 23]. The costs of the support mechanisms for RES are recoverable from ratepayers—the consumers that purchase electricity from the DISCOs. Further, the RA may penalise DISCOs financially for failing to meet their RES mandates [24]. The main beneficiaries of such a policy are typically commercially

¹The terms ‘DNO’ and ‘distribution system operator (DSO)’ are sometimes used interchangeably in the literature to refer to the entity that is responsible for developing, operating and maintaining the distribution network, and does not participate in market activities. Some contemporary use of ‘DSO’ emphasises an expanded or isolated role of a neutral market facilitator. The role of a DISCO consists of network operation and other functions of the DNO as well as the sale of energy. The DNO recovers capital and O&M costs through connection and use-of-system charges whereas the DISCO’s charges include the costs of generation.

focused generators that seek to sell energy, but are not owned by the DISCO. This type of generation is known as independent generation or independent power production (IPP) [25,26].

Third, a significant share of DISCO revenue is composed of volumetric sales from electricity consumption. However there is a risk to this income because consumers may turn into producers [27]. This means that rather than buy energy supplied by the DISCO, consumers will meet some or all of their demand through electricity generated onsite, referred to as self-generation (SG).

In current DG planning practice there is no deliberate consideration or coordination of the underlying drivers of the above-mentioned costs [28]. Alternatives to network reinforcement, such as active network management, do not form part of the business-as-usual, network planning process. Budget determinations for RES support instruments and RES induced revenue loss are worked out in isolation [29]. The non-compliance penalty for RES mandates may not be flexible—it is not adjusted in harmony with limited available RES capacity [30]. Put together these factors risk exaggerated network costs, inaccurate RES budget estimations and unfair profit erosion.

There is extensive research on the impacts and planning of DG, with most studies incorporating technical issues such as voltage and thermal loading effects [31,32]. A number of studies extend the focus to extracting latent network capacity through active network management (e.g. DG curtailment) [17,33]. Further, advancements in active management have been demonstrated to be practically feasible [34,35], meaning network operators can now manage interruptible DG connections in real-time in capacity constrained distribution networks. Augmenting traditional planning approaches with ANM, will enable DISCOs to promptly connect and manage increased DG in constrained networks cost-effectively. This is not the case with fit and forget approaches that are used currently by DISCOs, which offer DG investors more costly network reinforcement as the only way to obtain access to the network [28].

However, there is a lack of capacity allocation methods that: incorporate both temporal power and accumulated energy curtailment given allowable bounds; and compute suitable DG capacity and curtailment that provision for practically relevant DG classes

(i.e. IPP and SG) and objectives that reflect policy and regulatory needs more closely. This makes it difficult to predict optimally the capacity shares of each generation class. Another implication is that expected SG and IPP impacts on RES support costs may be far from optimal or exceed the allotted financial resources.

The regulatory regime paves the way for DISCO behaviour. But there is little work on performance-based regulation and its implications for RES integration. Simply knowing whether or not there are technical barriers for DG connections is not sufficient because DISCOs also have financial concerns that motivate their planning decisions. For example, under traditional cost-of-service regulation the DISCO has a throughput incentive. That is, the incentive to raise revenue by maximising energy consumption [36, 37]. But this runs into conflict with SG or onsite generation, which seeks to minimise energy imported from the network. So rather than promote SG, the DISCO may minimise it to protect their revenue and ultimately compromise wider RES goals and the just allocation of network capacity. This deficiency highlights the need to develop regulation methods that are performance-based and are able to remove or counter the throughput incentive.

Although a great deal of performance-based regulation research in existence deals with supply quality issues [38–42], the need for more emphasis on DG integration has not gone unnoticed. Recent studies have explored the impact of predetermined DG on known use-of-system charges, loss and load factor reward-penalty schemes and network investment planning [43, 44]. The regulatory mechanisms for mitigating the financial impacts of distributed photovoltaic (PV) generation are discussed in [27].

But there are questions regarding the combined role of SG and IPP allocation within regulated and constrained networks that must obey policy-derived RES obligation. In other words, there is no efficient method to coordinate SG and IPP allocation in constrained networks, and the collective impact of the quota obligation, RES support costs and energy sales erosion within these networks is unknown. The present work overcomes this limitation by developing explicitly the role of SG and IPP through the optimised viewpoints of the DISCO and the RA.

Overall, the work of this thesis is motivated by the need to produce the following

Chapter 1. Introduction

benefits for stakeholders:

- Cost savings for the DISCO and as a result its customers.
- Better understanding of the technical and economic impacts of renewable energy incentive schemes, regulation and ANM on network capacity allocation for different DG classes and their associated, adapted generation levels.
- Increased renewable DG integration—assists the transition to low carbon networks. Also, the use of novel cost-effective approaches will enable DISCOs to possibly receive incentives under some regulation frameworks.
- Customer service and satisfaction—more alternative framings will be investigated, leading to improved planning studies and feasible connection offers to an increased number of DG investors. There will be faster and cheaper customer connections when ANM is utilised to avoid or defer network reinforcement.
- Profit-preserving compliance—DISCO planners will be able to reach profit-preserving compliance, complying with mandates without compromising DISCO profits. RA-approved funding resources on the basis that profit is not excessive, thus protecting consumer interests. This reduces the chance that consumers will oppose rates assuming the RA sets a budget that factors in affordability.
- Integrated Allocation Study—ad hoc approaches can be replaced with an integrated tool that accounts for policy, regulation and operational aspects within a single framework. The results can be interpreted as a baseline for promoting RES capacity allocation among independent producers and consumers with onsite generation.
- Reduce information asymmetry—RAs commonly lack sufficient information to make optimal decisions about DISCO operations [45]. In this case the RA gains an analysis tool to enhance the quality of its decisions.
- Realistic target setting—The RA will be able to turn central planning goals into enforceable targets within a performance-based regulatory framework. The approach enables the RA to compute optimised incentives that drive DISCOs to

meet central planning goals. This is because the RA can determine in advance how much network capacity is available to RES and their financial impact on DISCO. Therefore the RA will set an RES mandate that is financially fair to the DISCO and affordable for consumers.

This next section summarises the novel aspects and contributions of the work presented in this thesis.

1.2 Main Ideas and Contributions

The focus of this thesis is on contributing detailed models of SG and IPP allocation combining the relationships between energy retail, policy instruments, regulation and network operation. These are some of the aspects informing DISCO decisions. The interested reader can refer to [46] for an exposition of the distribution network planning process.

Consider the generation capacity and location allocation problem, (1.1). Let Ψ be the generation capacity given a set of candidate locations.

$$\underset{\Psi \in \mathcal{A}}{\text{maximise}} \quad \text{Energy Revenue} - \text{Energy Cost}, \quad (1.1a)$$

$$\text{subject to} \quad \text{Network Constraints}, \quad (1.1b)$$

where \mathcal{A} defines the generation bounds. The formulation (1.1) is from the perspective of an actor seeking to maximise its profit within the power network context. It is common within many network optimisation applications including generation expansion (with or without network constraints) at the transmission system-level considering electric power markets [47], and distribution network DG allocation [26]. The present work is concerned with the latter problem, particularly the interests of the DISCO and the role of the RA, which ensures the DISCO also pursues the interests of public policy and the DISCO's customers.

Suppose (1.1) represents the perspective of the DISCO and DG capacity as the decision variable. The amount of DG allocated network capacity is influenced by several factors. If it assumed retail revenue and wholesale energy costs are fixed and DG

energy costs are equal to wholesale market (upstream) energy costs, (1.1) equivalently minimises energy losses. If DG energy is sufficiently cheaper than upstream energy then (1.1) maximises DG energy. If the energy revenue is not fixed but decreases with rising DG, (1.1) minimises DG energy. Therefore the DISCO displays varying behaviour, leading to different capacity allocations for DG.

On the other hand the RA aims to guide the DISCO towards meeting central RES policy goals i.e. connect renewable DG in line with a specific target and within budget. An arising question is how the objectives of the DISCO and the RA can be aligned. It turns out the RA can exercise some control by positively incentivising or penalising the DISCO towards performing as desired. Existing studies have commonly focused on policy issues affecting SG in view of its associated costs and benefits. In [27, 48] the financial impact (including policy support schemes) of SG is considered but not within the context of network operation and capacity allocation. Network interaction of SG and IPP is, therefore, also ignored. Others (e.g. [26, 32]) focus on network operation without considering the effects of onsite load. This leads to the novel contributions presented in this thesis.

Specifically, the problem (1.1) is recast to characterise SG, that is DG that reduces retail revenue, in addition to IPP, DG that pursues commercial interests but meets public policy goals for RES. Define \mathcal{B} and \mathcal{C} as sets of SG and IPP constraints that must be satisfied by the computed allocation. Let $\Psi_{\text{SG}} \in \mathcal{B}$ and $\Psi_{\text{IPP}} \in \mathcal{C}$ represent the SG and IPP capacities at candidate locations. The reformulated allocation problem is given by

$$\underset{\Psi_{\text{SG}}, \Psi_{\text{IPP}}}{\text{maximise}} \quad \text{Energy Revenue} - \text{Energy Cost} + \text{Incentives} - \text{Penalty}, \quad (1.2a)$$

$$\text{subject to} \quad \text{Financial Resource}, \quad (1.2b)$$

$$\text{Network Constraints}. \quad (1.2c)$$

The incentives in (1.2a) are functions of self-consumed and exported energy at SG sites. The penalty function defines the mechanism for enforcing the quota obligation for renewable DG integration. When existing customers invest in SG the DISCO stands

to lose income from energy sales when the energy produced is consumed locally. As penetration levels rise this may have the effect of higher electricity costs for consumers without generation facilities as DISCOs try to maintain profit levels. The same applies to all renewable DG when its cost of energy exceed that of that of wholesale market. Therefore DG capacity allocation incorporating the balance of profits for retailers to minimise consumer costs, is an important aspect to consider. These costs impose a budgetary constraint (1.2b) on target-oriented DG integration. Using (1.2), it is shown in this thesis how administratively set incentives for SG and IPP impact the DISCOs profit within constrained networks. Further, a comparison with the approaches of capacity maximisation and rule-based allocation is conducted.

It is possible the DISCO's revenue can be maintained, despite fluctuations in energy sales, by means of a revenue regulation scheme known as decoupling [18]. Its limitation is that it lacks a performance incentive mechanism that readily ties the revenue to policy instruments such as the quota obligation. More optimised regulatory mechanisms are thus launched, forming further contributions within this thesis. Let \mathcal{D} and \mathcal{G} represent the set of incentives and curtailment constraints, respectively. The regulated SG and IPP optimisation models are formulated as

$$\underset{\Psi_{SG}, \Psi_{IPP}, \vartheta}{\text{minimise}} \quad \text{Profit Deviation,} \quad (1.3a)$$

$$\text{subject to} \quad \text{Financial Resource,} \quad (1.3b)$$

$$\underset{\varphi}{\text{minimise}} \quad \text{Operation Cost,} \quad (1.3c)$$

$$\text{subject to} \quad \text{Network Constraints,} \quad (1.3d)$$

where $\vartheta \in \mathcal{D}$ denotes the positive incentive and penalty rates and $\varphi \in \mathcal{G}$, curtailed generation; $\varphi = 0$ for the first regulation optimisation model. The first regulation optimisation model, (1.3a)-(1.3b), (1.3d), relates to finding incentives (ϑ) that allow the DISCO to conditionally maintain profit while introducing renewable SG and IPP according to specific RES targets or quota obligations and constraints on financial resources. The objective (1.3a) models the deviation of (1.2a) from the allowed or required profit of the DISCO, which is linked to the ratemaking case. The results of

this optimised regulation model are compared with those of the standard decoupling mechanism.

The role of regulation is central to presenting a unified perspective on stakeholder needs. Meeus and co-authors provide a vision of smart regulation that aligns best with the proposed regulation models, that “Smart regulation reconfigures the incentives and coordination tools of grid companies and grid users and aligns them towards the new policy objectives” [49]. Smart regulation herein requires correction of some existing network incentives and introduction of mechanisms to facilitate the transformation of passive to active networks. The work of [17] is a characteristic example of related studies that demonstrate the impact of ANM in capacity allocation. However, such models have not yet accounted for SG/IPP, policy and regulation impacts. The second regulation optimisation model (1.3) presented in this thesis adds an operation layer to the first so that efficiencies enabled by ANM can be exploited. These efficiencies stem from extracting latent DG capacity before having to reinforce the network. At the lower operation layer, the control variable is curtailed generation. Further layers can be added, such as volt/var control to reduce energy loss cost and eases voltage constraints.

The optimisation models address the perspectives of different stakeholders with focus on the following requirements:

- DISCO—The presence of more than one exclusive incentive mechanism for DG connections poses an unexplored challenge in distribution network planning. As DISCOs look to offer viable connection options to more DG customers, there is a growing need for accurate representations of costs and benefits of different DG connections.
- Independent power production (IPP) and self-generation (SG)—DG investment is considered attractive if it produces profits in the project’s lifetime after revenue from energy sales as well as capital and operating costs have been taken into account. In the case of self-generation, the retail cost of energy is also an important factor. The incentive schemes explored in the proposed models must produce economically viable investments for IPP and SG plant owners.

- Consumers—The costs of renewable DG incentive schemes are mostly passed through to consumers. To minimise the total cost incurred by consumers, it is necessary to consider factors such as obligation over-compliance and the cheapest combinations of generators (IPP and SG). This implies that DISCOs have to determine optimal sizes and locations of IPP and SG to meet cost constraints rather than maximise profit at any cost.

A curtailment strategy is developed to deal with independent power production and self-generation. Apart from the DISCO's interests, the allocation of capacity to DG applications qualifying for any of the various incentives has cost implications for independent developers, SGs and pure consumers.

A performance-based regulation model aimed at achieving cost-effective RES integration plans delivered by DISCOs (serving energy consumers, IPP, SG) is proposed for the work of this thesis. Regulated DISCOs are increasingly required to simultaneously meet RES targets and keep procurement costs below predetermined limits. Furthermore, the targets are becoming increasingly specific, requiring the connection of SG and IPP.

The optimisation model provides a decoupling mechanism that makes it possible to connect both SG and IPP according to specific individual targets. Incentives for IPP and SG are calculated jointly and reflect the sharing of limited network capacity.

However, when candidate DG units comprise IPP and SG, there is a risk that RES targets will not be met without exceeding cost caps associated with support schemes or violating network constraints. This is because, currently, there is no predictive (or forward-looking) mechanism that jointly and optimally relates RES targets to IPP, SG and the associated financial constraints (i.e., support scheme costs and DISCO profits). Moreover, there is little work on reward/penalty mechanisms (RPMs) for RES network integration target setting.

A predictive approach is presented as part of the work of this thesis, developed on the basis of network modelling, that employs an RPM that DISCOs encounter as a result of RES policy and regulation. The regulation optimisation formulation attributes the additional costs experienced by DISCOs to the total cost of RES programmes and

reveals the link to incentives required to maintain profit levels after the integration of RES. The incentives are reflective of innovative operational approaches (beyond ‘business as usual’) available to DISCOs in the form of active network management. Specifically, a penalty scheme suitable for quota obligations commonly prescribed in RES policies, and revenue generation and recovery mechanisms are designed considering generation curtailment and volt/var control.

The regulation optimisation model considers optimised RES planning, which is described here as determining RES (IPP and SG) capacity and location that preserve DISCO profit and satisfy RES scheme cost requirements. The DISCO complies with SG minimum connection requirements as part of licence conditions that permit network access for any new connections. The quota obligation provides another way to comply by way of penalty payments. This approach, developed through the work of this thesis, closes the gap between DG programs and constrained network studies, promoting better estimation of lost revenue and profit. In other words, the question of the integration cost of customer-owned DG and how much of it should be recovered from customers is addressed. That is in addition to rewarding desirable allocation plans by adapting compliance mandates to innovative solutions such as the use of ANM.

1.3 Research Method and Activities

A comprehensive literature evaluation was conducted in respect of the above stated DG capacity allocation and regulation problems. It progressed in an iterative manner together with the subsequent activities illustrated in Fig. 1.1. The overall procedure is briefly described as follows:

- Formulate a computational model incorporating technical and economic aspects of DG planning from the perspectives of the DISCO and its customers.
- Derive appropriate power system component models. IPP and SG are represented by two different configurations: a sole generator model is adopted for IPP while SG is represented by a combined generator and load model.
- Formulate an ANM model with representations of curtailment for IPP and SG.

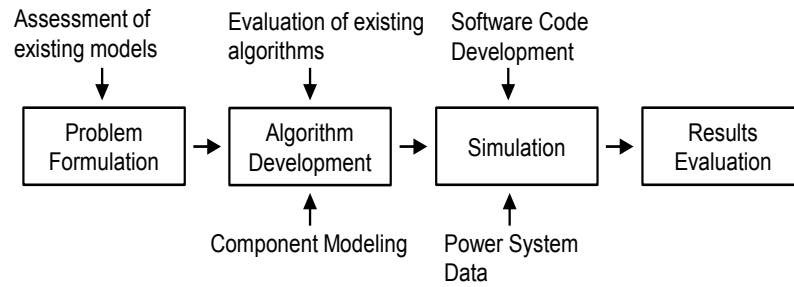


Figure 1.1: Research method.

- Develop an optimisation model to solve the DG planning problem in networks with ANM capability.
- Investigate and apply or develop suitable solution algorithms to solve the DG allocation problems from the perspectives of the DISCO and the RA. This step involves an assessment of power flow and optimisation algorithms in terms of complexity, convergence behaviour, flexibility and feasibility of results. The optimisation algorithm must be capable of handling multilevel problems and various types of objectives and constraints. For instance, IPP and SG impose various distinct constraints on the problem. In fact, there are two additional sets of temporal and binary constraints. One defines the import and export behaviour of SG and the other reflects the compliance mechanism associated with quota fulfilment. Another constraint is the capacity restriction for generation under the quota obligation mechanism. Allocation of capacity in this respect must take into account the fact that there is a nonzero minimum cap imposed on potential generators. The implication is that discontinuities are added to the capacity constraints.
- Identify a suitable software tool, translate algorithms into software code and carry out simulations. Representative distribution networks are selected for case studies. Apply optimisation algorithm.
- Extract and interpret result data. Evaluate technical and economic performance of proposed model in relation to traditional approaches. This step includes sensitivity analyses of major system parameters.

1.4 Outputs Arising From Thesis

Parts of the material presented in this thesis have appeared in previous publications. The network integration model for SG and IPP in Chapter 4 was first published in (1). Likewise, the voltage and reactive power control method in Chapter 6 appeared in (2). During the development of this thesis, the author also published another journal article (3), on energy end use by reconfigurable charging networks.

- (1) L. Mokgonyana, J. Zhang, H. Li, and Y. Hu, “Optimal location and capacity planning for distributed generation with independent power production and self-generation,” *Applied Energy*, vol. 188, pp. 140-150, 2017.
- (2) L. Mokgonyana, J. Zhang, L. Zhang, and X. Xia, “Coordinated two-stage volt/var management in distribution networks,” *Elect. Power Syst. Res.*, vol. 141, pp. 157-164, Oct. 2016.
- (3) L. Mokgonyana, K. Smith, and S. Galloway, “Reconfigurable low voltage direct current charging networks for plug-in electric vehicles,” *IEEE Trans. Smart Grid*, to be published, doi: 10.1109/TSG.2018.2883518.

1.5 Outline of Thesis

The remainder of this thesis is organised as follows:

Chapter 2 provides a review of key concepts and developments in the existing literature and practice of DG integration within power networks. The highlighted aspects relate to RES policy, network operation and regulation. It finds that to fully integrate these aspects cost-effectively a more inclusive and optimised RES allocation approach is needed.

Chapter 3 paves the way for explicit SG and IPP modelling with a preliminary mathematical description, and a case study of OPF in the context of capacity allocation. It introduces the core computational algorithms employed in the numerical studies, starting with a primal-dual interior point method. This is followed by a cost and benefit formulation, which leads to an explicit optimisation model for SG and IPP

Chapter 1. Introduction

allocation. The model is solved by swarm optimisation, the second core algorithm in the thesis.

Chapter 4 presents an elaborate formulation and case study of the DISCO's perspective when it is exposed to various incentives. For every set of incentives the DISCO seeks to maximise its profit. This behaviour sometimes holds severe implications for SG and IPP allocation. For an overseeing RA, the intent will be to ensure that RES mandates are met and that the DISCO's profit is neither eroded nor excessive.

Chapter 5 describes and implements the mathematical model of the RA's viewpoint. The RA must know what incentive and penalty levels to set so that the DISCO not only meets its RES targets but also receives a fair profit. Within this framework, the RA must understand when the RES mandates are limited by a constrained network and determine incentives amenable to this restriction.

Chapter 6 develops a comprehensive regulation model for ANM incorporated networks. The chapter begins by describing the method of coordinated volt/var control and evaluating its utility, which is removing voltage constraints and minimising energy losses. This is followed by a mathematical description and numerical study of the RA model when curtailment of SG and IPP is permissible.

Chapter 7 presents the summary and conclusions, highlighting the significance and implications of the work. It also provides possible practical implementations, extensions to the proposed models and potential research directions.

Chapter 2

Background

2.1 Introduction

There are numerous reasons for power companies, consumers or investors to include DG in their portfolio of solutions. Decisions can be driven by, among others, network constraints, policy, and DG's cost saving potential. The regulatory environment also plays a role in how DG is perceived. Here the requisite concepts of distributed generation integration are described, focusing particularly on the context for renewable DG within which the work presented in subsequent chapters is placed.

2.2 Distributed Generation in Power Networks

Methods quantifying the network benefits of DG are described through the lens of optimisation. For RES, other benefits such as decreased public health risk are recognised by way of centralised policies. Considering methods to maximise the value of DG, ANM is explored as an operational alternative to network reinforcement. ANM is typically framed as an optimal power flow problem on the network scale.

2.2.1 Cost Saving Benefit

There are plenty of studies on the grid connection of new DG, which can be viewed in terms of allowable decisions and objectives. The approaches described in [50] and [51]

determine optimal locations and sizes of DG units to maximise savings arising from deferral of network upgrades, minimise energy loss and improve reliability.

The business-as-usual approach by DISCOs to network planning is to reinforce their networks as soon as there is expectation that statutory voltage limits will be exceeded or existing components overloaded. Reinforcement refers to line, transformer and other component upgrades or connection of additional elements.

When a DG supplies power, but at levels lower than the total network demand, the total power flow into the network decreases relative to the situation with zero DG supply. Conversely, DG power injection exceeding network requirements increases the power flow in the opposite direction, but under load growth, this flow decreases until DG power is completely absorbed. If growth stops thereafter, the power flow increases again towards components limits. The deferral benefit clearly depends on network conditions [52]. In this sense it is critical to contextualise the capability to defer investment. As has been suggested following an investigation of practical distribution circuits, the deferral value of distributed PV generation can be insignificant when the feeder peak load is less than its peak capacity [52]. This was found to be the case for many distribution feeders in a California service area [52].

A DG-triggered deferral model presented in [53] targets distribution networks experiencing load growth. The deferral benefit is quantified in terms of time and monetary values. The overall monetary benefit is expressed in relation to DG capacity per kVA. The deferral time is a function of the DG size and the growth rate of the load. DGs increase the time after which investments have to be made. The time is defined as the time it takes feeder currents to reach levels observed prior to DG installation. General expressions to quantify the deferral benefit mathematically are formulated on the basis of current sensitivities and time value of money. DGs also have an influence on bus voltages, but this is not explicitly stated mathematically although it is used to describe some results. The distribution network is sectionalised into the feeder backbones and laterals, all of which are referred to as feeders. This strategy goes with the assumption that upgrades in all the feeder groups are carried out at the same time. Also within this context, an upgrade means the next higher current rating selected.

The work of [50] develops an assessment criteria for DG integration based on the benefits that the DISCO receives. The benefits considered are deferment of network reinforcement, decreased energy loss cost and improvement of reliability. Network reinforcement is divided into lines as well as protection and metering upgrades. The cost of energy losses is deemed to reflect the variability of load, DG supply and energy price. However, the cost is not calculated for every time interval but for scenarios determined from a joint DG model. The network interruption cost requires that islanded network operation be permitted. Two modes are then possible; the distribution network can be fed from upstream generators during normal operation and DGs during faults which remove the link to the transmission network.

The contribution of [14] is the consideration of contingencies, also known as security constraints, and the development of a multistage method to quantify the investment deferral impact of DGs. Security constraints are satisfied by ensuring that voltage and thermal limit violations are avoided in normal and contingency (N-1) scenarios. Also, the deferral benefit is calculated from actual times of investment. The study incorporates DG reliability, although it utilises a simple equation to estimate the power output of different DGs during a circuit outage of certain duration. In general, firm generators contribute more power during outages than non-firm generators such wind power plants. The evaluated planning options comprise two types of reinforcement: connection of an extra line or transformer and replacement of an existing component with one of higher capacity. To find a suitable expansion plan, a greedy heuristic algorithm called successive elimination method is applied [14]. It begins by connecting all possible expansion options and evaluating the resulting voltages and flows. If there are no constraint violations, the least cost-effective branch is removed. This procedure is repeated until removal of any branch causes constraint violations in either normal or N-1 operation. Investment deferral is quantified with a multistage model since the requirement of different expansion strategies occurs in different years. The deferral is defined as the present value of the investment in reinforcement for a DG-less network minus the present value of the investment when DGs are installed. Although this part of the model takes into account discounting, this capability is not incorporated in the

step involving successive elimination of expansion options. Results demonstrate that investment deferral varies significantly with DG location when one DG is installed.

In [51], two objective functions are defined in order to adequately represent the preferences of distribution network operators (DNOs) that are allowed to own DGs and those prevented from DG ownership (unbundled DNOs). When a DNO is capable of investing in DGs, it is important to evaluate the costs and income due to the installations. The cost component comprises operations and maintenance, fuel and capital costs. The income is represented by the network deferral benefit, revenue from energy sales and finally, an incentive for loss reduction. The objective for unbundled DNOs is simply the sum of capacity payments for DGs connected and a loss incentive component. The network deferral benefit is ignored. The model caters for voltage and thermal constraints. The optimisation model is solved using a multi-period optimal power flow (OPF) procedure developed in previous studies. In its treatment of DGs, the method presented in this paper precludes variable DGs, dealing instead with firm units. The selected case study focuses on an 83-bus distribution system with gas and diesel DG as investment options. The simulation results demonstrate that the loss incentive is the least influential part of the objective function for a DG-owning DNO. In some scenarios optimal solutions produce more losses than the reference case, which is a solution with zero DG production. For an unbundled DNO, the loss incentive is more prominent but limits DG capacity to relatively low values compared to its DG-owning counterpart. Moreover it turns out that accurately evaluating losses in the presence of variable DG requires that traditional methods be adapted. Power loss calculations directed only on single demand-generation scenarios (e.g., minimum demand-maximum generation) can misrepresent the impact of variable DG on losses [13]. The variability of demand and generation is better captured by analysing *energy* losses with reflective temporal resolution.

It is found in [54] and [55] that there are additional benefits of DG connection, in the form of use-of-system charges, capacity and loss reduction incentives overseen by regulators. In [26], the profit of a DISCO is maximised by strategic sizing and placement of independent DG while maintaining project viability.

The model proposed in [56] minimises the cost of power purchased from generation companies (GENCOs), the capital and operating costs of DG units owned by the DISCO, and the costs of network operation and unserved power. In [47], the objective is to maximise social welfare among DISCOs and GENCOs, and to maximise profit for the DG owner. The interaction between a DG owner and DISCO can also be treated as a bi-level problem whereby the DG owner's profits are maximised first followed by the DISCO's cost of energy [57]. The work presented in [58] models the role of a central planning authority aiming to encourage GENCOs and local DISCOs to achieve pre-specified targets for renewable energy sources (RES). The resulting incentives ensure the viability of a mix of various technology investments.

Seeking to optimise many objectives that arise in DG planning inevitably creates contradictions. This creates the need for flexible methods that equip the planner with the capacity to select the best compromise. As such, conflicting objectives can be accommodated within a multiobjective framework [59].

2.2.2 Policy-Driven DG Planning

While the benefits of DG in distribution systems have been widely studied, there is a lack of focus on the implications of renewable energy policies from the DISCO's perspective concerning independent DG units. The influence of quota obligations and REC markets have on RES capacity planning conducted by developers has been studied in [60]. Market participants studied are RES and non-RES developers. The latter have an obligation to purchase RECs from the RES developers. Using various competitive market models, the study explains the relationship between the quota obligation level, non-compliance penalty and the RES development decisions. Of importance is that it is possible to find a non-compliance penalty that produces the same social welfare as when determined by a central planner.

The formulation in [61] considers capacity expansion planning in the presence of renewable portfolio standards and carbon tax mechanisms. Another study investigates the impact of the aforementioned mechanisms plus feed-in tariffs (FiTs) and emission trading on expansion planning [62]. Although these models take environmental policies

into account, they are solved from the perspective of a GENCO or a central planner. Others are designed mainly for generation expansion planning on transmission networks [63]. The renewable policies considered are renewable portfolio standards with mandatory requirements. Besides renewable energy, coal generation is taken to be the least cost alternative without any policy intervention. The impact of FiTs, carbon tax and cap-and-trade mechanisms on DG investments by DISCOs and independent investors is studied in [64], with the objective being to maximize the profit from the sale of energy.

In contrast, this thesis proposes an approach to DG location and capacity planning, which simultaneously incorporates the impacts of renewable energy policies according to the viewpoint of the DISCO, which does not own the DG units. As a result the DISCO avoids the investment and development responsibilities, which are taken up by the suppliers. This approach is in line with the many instances whereby the DISCO coordinates generation by other suppliers rather than their own facilities [65], [66].

In particular, a framework is introduced, representing the practical case in which DG is classified as independent power production (IPP) or self-generation (SG) [66]. IPP accounts for large DG units that solely produce electricity. SG represents existing customers seeking to invest in on-site or behind-the-meter generation, which is physically positioned closer to their load. In the order of growing market maturity, the adoption of SG can be driven by incentives (e.g., FiTs), the costs of SG being lower than retail prices, and competitiveness of SG on the wholesale market. Renewable SG deployments have been dominated by PV generation; in comparison small wind systems (< 50 kW) face various challenges, among them height restrictions and concerns about visual aesthetics [67]. Regulators and policy-makers are beginning to address the barriers to small wind installations and provide support for their sustained growth. Thus the outlook for on-site wind DG is positive with residential, commercial and midsize turbines deemed to be increasingly viable [68].

IPP is promoted through a quota obligation scheme [20]. The scheme requires that DISCOs supply a portion of their total load from renewable sources or make an alternative payment to a regulatory body. The quota obligation mechanism is

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accompanied by an obligation for DISCOs to purchase renewable energy certificates from RES through long term contracts or the certificates market [20], [69]. Examples of a quota obligation mechanism are the Renewables Obligation in the UK and the Renewable Portfolio Standard in the US [70], [71]. The US power market is made up of a multitude of utilities (cost-of-service) regulated by government agencies, competitive (restructured) markets and hybrid providers combining aspects of regulated utilities and competitive markets. Utilities or retailers in the different markets are held to varying cost limitations for RPSs.

The costs of quota mechanisms are described and limited through various measures [24]:

Annual Retail Revenue Caps. This mechanism allows utilities' expenditure on RES to reach a specific percentage of the utilities' yearly revenue requirement. States that employ this mechanism differ by costs allowed to count towards the cap and whether the cap is voluntary or compulsory. For example, some jurisdictions do not permit the inclusion of alternative compliance payments (ACPs) in the RES cost calculations.

Annual Rate Cap. A rate cap limits the periodic rate increase in different customer classes based on actual or projected customer costs. This approach raises/reveals mostly the same questions as the retail cost; what are the qualifying costs of compliance; and is the cap binding or not?

The main critique of retail revenue and rate caps is that they may not be effective because cumulative rate increases over time can be much higher than anticipated. Also, the role of regulation is vital in ensuring utilities undertake least-cost compliance plans.

Surcharge. Another way to track costs is to apply a surcharge to customer bills. The surcharge recovers RPS compliance costs through a fixed charge or a surplus rate based on energy usage of different customer classes. Surcharges require less administrative effort because they avoid rate cases. However, the fact that regulation is less stringent than in rate cases suggests that least-cost measures can be overlooked.

Expenditure Cap. Utility compliance costs can be limited in total through a funds cap. Below the expenditure cap, utilities can recover RPS costs in their rates. In California, the regulating body assesses the eligibility of power purchase contracts (PPAs)

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taking into account the difference between the levelised contract price of a project and the market price referent. According to the California public utilities commission, this method supports RPS goals, promotes least-cost RES projects, and apportions funds transparently. The disadvantages of an expenditure cap relate to regulation and RES targets. The regulating body must approve every PPA. Furthermore, it will be difficult to meet high RPS targets since utilities must petition the regulating body if the cap is to be exceeded.

Alternative Compliance Payments. ACPs are commonly found in restructured markets. These payments usually go towards a central fund, which in some instances aid RES development. When an ACP is recoverable, it is effectively a cap for the compliance price. Otherwise, it is a non-compliance penalty. As long as the ACP is recoverable, electricity providers will be inclined to opt for RECs or PPAs until the price is the same as or exceeds the ACP price. Although they have the potential to shield consumers from high prices, poorly set ACPs can have compromise RPSs. Setting the ACP price too low will lead to low procurement of RES. On the other hand, setting the price too high will raise consumer rates even if providers fall short of (meeting) RPS targets.

Contract Price Cap. Some utilities are not obligated to purchase electricity from RES if the price is higher than a certain percentage of alternative generation. This approach protects consumer costs by keeping RPS compliance costs near the cost of viable alternatives. However, it tends to cause uncertainty for, among others, utilities, consumers and project developers.

Regulation Discretion. In some electricity markets, none of the above mechanisms is in place. Instead the regulating agency has the discretion to exercise controls if costs become extreme. The agency may judge compliance costs for prudence and reasonability in ratemaking cases. Alternatively, the agency may review every RES contract according to specific criteria such as environmental costs, state economic benefits, and resource diversity. Moreover, agencies may be given the authority to freeze rising RPS targets if costs are equivalent to or higher than caps. Utilities may be granted waivers on grounds of cost-related consumer impact. The disadvantage of agency discretion

is that the decisions of the agency may be subjective, politically driven, lack fairness or prioritise utility interests over those of customers (such as investment return over customer costs).

SG is typically supported by net-metering or the FiT incentive scheme. The impact of net-metering arrangements on cost-recovery of DSOs/DISCO and cross-subsidies between network users is studied in [72]. Net-metering alternatives are presented according to differences in metering, accounting and billing. Metering aspects include meter placement and measured quantities (e.g. kWh and kW). Issues of accounting involve the charging approaches for consumption and production. Rolling credit is used to describe the difference in consumption and production over time. These variations can be determined hourly, daily, even yearly. Finally, billing provides insight into the variables used to design tariffs, formed by energy, capacity or fixed charges. The study finds that DSO income declines as rolling credit increases under volumetric energy charging. As DSOs correct this income disparity through additional charges or update tariffs, there will be cross subsidies from consumers without generation to those with generation. For a network of 100 users, the cross subsidies can be substantial, reaching 20% of DSO income annually. The potential solutions suggested are: more explicit incentives for temporal consumption and production; replacing net-metering with schemes such as FiT; improved tariff designs to reduce dependence on volumetric energy charging because actual costs depend on capacity.

FiT schemes offer certainty through purchase of power at fixed rates and guaranteed payments over long periods [20]. They have thus achieved significant adoption of renewable energy resources in countries such as Denmark, Germany and Spain [21]. Although widespread, the schemes encompass several arrangements, which take different forms in different countries. FiTs are typically issued for generation and/or exported output. Various rates are possible if supported by suitable meter configurations. The generation and export rates can be regarded as incentive signals to DG owners to either consume more or less energy whenever there is local generation [73]. Heavy emphasis on generation rates rewards on-site consumption—DG owners benefit more from consuming the energy produced locally. Conversely, marginally high export rates encourage

owners to use less energy and export it instead. In the UK, approved generators receive payments for all generated energy and extra earnings if a portion of the energy is exported to the network [74].

The import and export variability of SG cause changes in revenue from energy sales, whereby revenue erosion is mitigated partly through recovery mechanisms [48, 73, 75]. DISCOs recoup the revenue lost due to SG integration from ratepayers. Hence promoting DG capacity and locations that maximise profit, the cost impact on ratepayers will be reduced. Under these circumstances, there are financial implications in regards to any action the DISCO takes with respect to renewable DG integration. It is therefore crucial to distinguish between IPP and SG.

However, none of the above-mentioned studies prescribes a model that considers binding RES quota and the combined impact of IPP and SG—on-site generation and energy consumption—on DISCO costs and revenues in the context of location and capacity planning for new DG connections.

This thesis is devoted to power distribution systems utilising FiTs to support renewable energy SG and quota mechanisms to promote renewable energy IPP. Both are incorporated as part of a capacity optimisation planning model through which the DISCO is primed to respond strategically to renewable energy policy. Given renewable energy quota, network and DG connection constraints, and the DISCO's viewpoint, model presented herein determines the locations and capacities to allocate to SG and IPP such that the profit of the DISCO is maximised. In addition, the objective function encompasses a financial penalty that varies with RES deployment, profit from the sale of energy, cash flow from incentives for lost revenue, and energy exported from SG locations. Furthermore, the impact of each of the following parameters on DISCO profits and location of IPP and SG is analysed: renewable energy quota, SG net energy limit, revenue recovery rate, energy export rate and IPP capacity cap. In addition, it is shown in the base-case simulation analysis that the proposed model is superior to other planning approaches in terms of profit maximisation and DG constraint satisfaction for two different systems, the 33-bus system and the 69-bus system. The model is employed to show that the DISCO will achieve an increase of 23.7% in profits in the

presence of constrained SG and IPP and a quota obligation of 23%.

2.2.3 Active Network Management

ANM is defined as the use of remote control and communication technologies to control power, voltage and frequency profiles within electricity networks [76]. It has been referred to as a smart DG integration tool and a viable alternative to network reinforcement [77]. The recent field impact of ANM is summarised below.

Some commercial experiences of DNOs/DISCOs in managing increased DG connections to distribution networks are shared in [78]. Growing DG penetration eventually causes strain to the network, eventually requiring improvements to release additional capacity. Network improvements traditionally involve reinforcing or upgrading overhead lines, cables, transformers and adding other components. Depending on how the costs of improvements are allocated, their impact on investment viability of DG is appreciable. Connection charging is characterised by two methodologies, deep connection and shallow connection charging. Deep connection charging transfers the full cost of network reinforcement to DG investors. Under shallow connection charging, the reinforcement costs are shared among network users. Smart, alternative approaches to improve network access have been trialled with success in real transmission and distribution networks. For example, San Diego Gas (SDG&E) found that Dynamic Line Rating (DLR) increases transmission line capacity by 40 to 80% [79]. The Belgian Transmission System operator suggests the upper value can in fact reach 100% in conducive wind conditions [80]. DLR can also be complementary to existing ANM systems, potentially lowering curtailment by 48% [81].

ANM has already been found practically valuable in two respects. First, it has been used to connect DG quickly and inexpensively by six DNOs in the UK [35]. Second, some of the DNOs have also trialled ANM to defer network-wide reinforcement for existing customers.

ANM is realised through localised or centralised strategies. Localised strategies control DG or other controllable devices independently to restrain bus voltage, line or transformer flows within limits. The voltage and flows are monitored locally and active

and reactive power dispatched according to the measurements.

Centralised strategies accommodate numerous network assets (on-load tap changers, DG, capacitors etc.) in terms of monitoring and management. Control solutions of this form mostly use heuristic and optimisation models to produce coordinated control actions.

Despite the proliferation of *optimisation* applications in literature, the concepts are slow to take off in industry. The slow adoption is mainly down to concerns about maintaining satisfactory operation of the network. Indeed, DNOs have expressed the risks to setting up first-generation ANM schemes on their sites and integrating them with the broader system [35]. Consequently, research studies are beginning to validate the advanced ANM schemes for practical use. The validation of a real-time OPF-based control scheme is presented in [82]. An architecture is developed therein, interfacing a distribution network simulator with a network management system that dispatches DG and OLTCs using OPF. The scheme also imposes delays related with measurement and communication. The authors of [83] place emphasis on computations run every minute to account for RES variability. When the OPF has to be computed at the sub-minute timescale, the method proposed in [84] appears more suitable.

Prominent principles of access to support power management (curtailment) by ANM schemes are [78]:

Last-in first-out (LIFO). Generators are prioritised according to the date of connection or network access whenever curtailment is required. The order of disconnection starts with the generator in last place. Application of this rule requires no amendments in technology or regulation. This strategy does not allocate minimum curtailment and at its worst causes unnecessary curtailment [76]. On the other hand, according to [78] it does provide higher social optimality than others because the marginal costs are incurred by the last ranked generator. The higher variance in returns makes future projects less attractive.

Pro rata. Generators experience the similar levels of curtailment. It is fairer and raises viability of newer generation projects. However, marginal costs are shared between all generators. These costs imposed by the last-in generator would have not

been considered by existing generators. There is also uncertainty regarding volumes of curtailment to be expected over the long term.

Technical Best. Generation is adapted in the order that is most effective according to physical principles. The resulting control actions are optimised for network operation in terms of the defined objective (typically minimisation of curtailed energy) and constrained type [76]. Following this curtailment approach can cause bias against certain capacities and locations.

Market-based arrangement. This approach involves competitive bidding among generators. Curtailment is allocated according to the best price offers, i.e., lowest to highest price bids by generators [85]. The market-based principle allocates curtailment more optimally among the generators and reflects better the actual costs of curtailment.

The work of [77] follows a cost-benefit methodology to investigate how DNOs, DG owners and end users are affected by allocation of larger amounts of DG, and proposes an incentive to improve the allocation. ANM in the form of curtailment has provided significant savings in real distribution networks, allowing DG to be integrated at roughly 2% of the cost of reinforcement (£0.5m versus £30m) in one case. Similar savings have been recorded in other projects [86]. Smart integration of DG in distribution networks is described as the use of smart technical, regulatory tools and engagement initiatives. Smart technical tools include ANM and dynamic line rating, which improve the flexibility of the network and reduce connection cost. Smart engagement initiatives refer to commercial arrangements enabled by the application of smart technical tools. Typical opportunities are interruptible capacity offers tied with principles of access, reduced connection fees and quicker connection time for DG. Smart regulation involves evolving support mechanisms that have stimulated DG growth over time. Regulation considers the interests of different role-players. Funding schemes such as FiTs, RECs, and auctions have been used to promote the uptake of DG. In some regulatory frameworks DNOs are incentivised to possibly implement operational solutions instead of exclusive network upgrades requiring capital expenditure. This can lower the costs recovered from DG (connection costs) and end users (use of system charges). In previous studies, the benefits for DNOs are quantified assuming capacity incentives (£per

kW) exist for DG connections. The incentives relate to annual DG capacity as well as operation and maintenance [54], [87]. In the UK, these incentives represent costs which would be recovered through allowed revenues if DNOs knew the amount of DG to be granted network access *ex ante*. The benefits of DG owners refer to profit generated from energy supply revenues, embedded benefits and energy savings minus overall costs. Revenues are obtained from wholesale electricity sales and incentive schemes. Among the benefits embedded in incentive are lower carbon emissions. Embedded benefits are allocated cost savings for connecting to the distribution network rather than the transmission network; these include avoided balancing system use-of-system charges and the generator's share of transmission loss reduction. Energy savings constitute the avoided retail costs for energy that would otherwise be bought from suppliers in the absence of local generation. Generation and connection costs represent total DG costs. Generation costs stem from technology-related capital and operating expenditure. Connection costs vary according to the type of network connection *i.e.* firm or non-firm connection. A firm connection guarantees continuous network access but the generator is liable for costs to upgrade the network. A non-firm connection offers an interruptible connection without the need for network upgrades. Wider societal/consumer benefits are described as avoided balancing system charges, supplier's share of transmission and distribution loss reduction. Anaya and Pollit suggest that generators benefit the most out of all parties involved (DNO, DG and consumers) [77]. As a result, a smart connection incentive is introduced to reallocate the DG integration benefits. The incentive is a payment made by the generators to DNOs to encourage smart connection of DG. It is loosely based on the benefits of loss reduction and network reinforcement deferral, requiring implementation of smart network schemes to maximise its value. In addition to the DNO, the incentive benefits consumers when the cost of network reinforcement is socialised.

2.2.4 Optimal Power Flow

It is fairly standard in power network research studies to frame ANM as an OPF problem able to be solved by established and emerging optimisation algorithms [88–

91]. OPF computes the operating state of a power system by optimising a specific objective within given system and component constraints. It always includes power flow equations. AC power flow equations are often stated in polar form, using voltage magnitude and angle as state variables to fully describe steady state behaviour of balanced AC systems.

The objective can be defined in monetary, planning, operation or reliability terms. Possible objectives include minimisation of generation costs, losses and load shedding. OPF can have both continuous and discrete variables. Among potential variables are active and reactive power generation, transformer tap positions or ratios, line and capacitor switching.

The method has seen use in transmission and distribution systems. Specifically, a more general case of OPF is common in transmission operational planning. It is called the security-constrained OPF (SCOPF), and its formulation adds network contingency constraints to that of standard OPF. Contingencies define possible loss of one or more network components. An extensive review of SCOPF can be found in [92], [93].

The OPF problem is in the worst case difficult (formally NP-hard¹) to solve [95,96]. A key aspect of OPF is the mathematical formulation from which the solution method is established. The earliest formulations of OPF fall under the nonlinear programming (NLP) classification. Discrete variables are routinely assumed continuous in this formulation. NLP models accurately represent AC networks and provide locally optimal solutions barring the discrete variable approximation. Suitable algorithms for solving these models include trust-region methods, augmented lagrangian methods and primal-dual interior-point methods [97–99].

Given some settings, say, practical transmission systems, the power flow equations can be simplified. In particular, strong coupling exists between active power and voltage angle. That is, changes in active power influence changes in voltage angle. It is indeed true when the network is largely reactive and has little resistance. The same relationship is found between reactive power and voltage magnitude. Some OPF formulations take advantage of this decoupled association of active and reactive variables,

¹Non-deterministic polynomial-time hard, as defined in computing and complexity theory; see for example pp. 87 of [94].

creating decomposed subproblems which are solved sequentially in the optimisation process [100]. Another alternative formulation is called the DC-OPF. Its principle can be seen as an extension of OPF decoupling. The main assumptions are that there is a small difference between voltage angles at adjoining buses, and that the branch admittance is imaginary. Furthermore, the bus voltage are often approximated as 1 pu. Because the DC-OPF has linear constraints, it is amenable to problem size.

For networks having tree topologies i.e. radial distribution networks there exist relaxed OPF formulations that are fast and scale well with system size [101]. But these are not generalisable in meshed systems.

Some NLP formulations recast the OPF model as a convex problem with reduced nonlinearity [102–105]. The underlying principle on which they are based is that there is a rank condition that qualifies the presence of a zero duality gap in the OPF formulation. The advantage of convex formulations is that they provide a global optimum in polynomial time. And they offer the ability to check how far the solution is from global optimality through a valid lower bound on the minimum objective function value. This is unlike other NLP algorithms, which do not provide a measure of solution quality [106]. Numerical experiments reveal that some semidefinite relaxation solvers can be more robust than their NLP counterparts for large (10,000 buses and over) OPF problems [107]. Problem formulations based on convex relaxations do however require more modelling effort and can have slower computational speed for large OPF problems. In other cases, the relaxed formulations fail to give solutions that are “physically meaningful” [108]. Specifically, the solution of the relaxation may fail to satisfy Kirchhoff’s laws, which must hold exactly in order for the result to make sense on physical grounds. Some of the issues, particularly modelling matters are addressed in [109]. The dimension of the relaxed model can also increase substantially with problem size [110]. The convex programs are typically posed as semidefinite programs and solved with primal-dual interior-point methods [105], [111–113]. Other convex relaxations actively being proposed include second-order cone and quadratic convex relaxations [114], [115].

Local NLP optimisers solve the nonlinear AC OPF equations but encounter initialisation issues while convex approaches find the global solution to the relaxed OPF,

having limited applicability to a wider range of OPF problems. The two approaches can in fact be combined in a complementary manner to produce more useful results. In particular, initialising an AC quadratic program with a solution from a second-order cone program provides a faster, more accurate multi-period OPF [116]. These methods can also be combined with population-based algorithms to solve formidable nonsmooth and nonconvex problems. One such example is the combination of sequential quadratic programming and particle swarm optimisation (PSO) to solve the dynamic dispatch problem [117].

In summary, there are three main approaches in general that simplify the degree of nonlinearity in OPF. First, the OPF can be solved with methods that find optimal local solutions. Second, the power flow equations can be replaced with approximations as in the linear DC-OPF. Third, the problem can be relaxed by means of convex formulations.

2.3 Network Regulation

The DISCO typically operate its businesses under some regulatory oversight. The regulator must find balance between conflicting objectives. On the one hand, the regulator must show consideration for financial sustainability and prosperity and of the DISCO. On the other hand, it must ensure that the DISCO provides service of acceptable quality at the lowest cost. This section presents an overview of prevalent regulation approaches that are applicable to the power industry.

2.3.1 Cost-of-Service Regulation

A cost-of-service regulatory mechanism guarantees compensation for a DISCO, for all its costs of supplying electricity. Costs include fuel, operation and maintenance, capital as well as labour expenses. The DISCO's revenue requirement is based on the costs plus an allowed return on investment. Data for a specific test or historical period is used for the calculation. In general, the rate and revenue requirement formulae are given by the sum of costs, return, and tax. Rates are calculated by dividing the revenue requirement by the retailed units of energy. For different classes of customers, the rate is designed

according to the revenue requirement of the corresponding class.

The advantage of compensation derived from cost of supply is that the DISCO is not presented with opportunities to extract more rent over and above its costs and allowed rate of return. The disadvantage of this kind of regulation is that it lacks incentives for cost reduction or improved efficiency. The DISCO can recover its costs whether these are optimal or not.

2.3.2 Yardstick Competition and Light-handed Mechanisms

Yardstick competition permits the utility to set tariffs based on costs of other comparable utilities [118], [119]. The regulator conducts statistical analyses, which are then used to calculate the allowable revenue for every company in the group. In practice, yardstick competition requires extensive data revealing the group's costs and characteristics. The difficulties that arise are that the regulator must be able to draw similarities and thus identify efficiency opportunities that the companies have in common. In light-handed regulation, the utility determines tariffs and the regulator takes a supervisory role with the authority to enforce changes in tariff and rate design.

2.3.3 Incentive (Performance-based) Regulation

Traditionally, regulators seeking to maximise social welfare have to deal with information asymmetry. DISCOs have more information about their costs and opportunities. As the regulator learns from previous DISCO rate cases, its information improves over time. Under cost-of-service regulation, costs are observed but not examined for efficiency. Because cost-of-service regulation ensures that the DISCO is compensated for all its costs, there can be no way to stimulate cost reduction. In this case, customers are vulnerable to price increases even if the DISCO does not realise high profits from high costs. Also, there is an underlying throughput incentive whereby increased electricity sales yield more profit. In comparison with cost-of-service regulation, incentive regulation (IR) incentivises public or private DISCOs to enhance investment and operating efficiency for the benefit of customers. IR is intended to provide more effective stimuli to regulated companies in many areas including cost reduction, innovation, as-

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set investment, and network access. The common thread between IR approaches is their evaluation of actual performance against a reference or benchmark performance. Traditional performance areas of IR applications include reliability, plant performance and safety [120].

Price-cap regulation relies on the regulating agency setting a price in the initial year and then updating it for inflation and target productivity in future years, over a fixed period of time [121]. The initial price is calculated using a cost-based regulation approach. It thus sets a limit on the energy price, offering decoupling between utility costs and profits. Ideally, price-cap regulation incentivises the DISCO to reduce costs. An undesirable effect of price cap regulation is that if the utility maximises sales, conflicts will arise between this objective and those of measures such as demand-side management [122]. When the regulator is highly uncertain about DISCO costs, attempts to maintain financial viability will result in a high price cap. This will ultimately lead to excessive profits as the regulator anticipates costs higher than the DISCO's actual costs.

The DISCO's revenue has some variability over time. Its causes can be related to uncontrollable weather events or simply customer growth. An apparent strategy for the DISCO in this case will be to increase or avoid decreasing sales, thereby raising or preserving profit. Within revenue regulation, *decoupling* constitutes a mechanism that incrementally adjusts rates to remove the link between the revenue the DISCO is permitted to recover from ratepayers and the units of electricity sold. Rate cases determine the revenue requirement in advance, forming a basis from which decoupling takes place. Between rate cases, actual earnings are compared with the revenue requirement. If the amount earned is less than the revenue requirement, the DISCO can increase rates to level up. If the earnings are higher, the DISCO must refund its customers. Decoupling takes place periodically, for instance, annually or more regularly, with every billing cycle. Whereas actual revenues between rate cases fluctuate under cost-of-service regulation, prices instead of revenues vary when decoupling is applied. This mechanism thus removes the throughput incentive.

Another way to regulate revenue is to implement a very limited form of decoupling,

which is called the lost revenue adjustment mechanism. Under the lost revenue adjustment mechanism, a DISCO is allowed to recover revenues lost as a consequence of measures such as energy efficiency (EE) initiatives [123]. This adjustment does not depend on the total revenue but isolates the financial contribution of specific programs. In other words, lost revenue is still recovered even if the total revenue ends up exceeding the DISCO revenue requirements. The decoupling and the lost revenue adjustment mechanisms are closely related to the regulation optimisation model presented in this thesis. What sets the proposed mechanism apart is that it is based on performance, aiming to restore the required financial state of the DISCO provided specific performance objectives are met.

2.3.4 Key Performance Areas

Supply quality is a known important area of concern in the power industry. It is commonly described in terms of reliability, voltage quality, and customer satisfaction [118]. Reliability is indicated by continuity of supply measures such as the frequency and extent of power outages. Voltage quality relates to minimising voltage disturbances that adversely affect end-use devices and equipment. An example of a customer satisfaction measure is the service provision time following new requests for service. Overly promoting cost reductions may gradually weaken the quality of electricity supply. It is thus imperative to create targets linking DISCO revenues to the aforementioned performance areas. The result is a trade-off between cost efficiency and supply quality. Quality of service initiatives are stimulated with RPMs. RPMs are financially impactful, decreasing or increasing utility revenues in line with performance. The design of RPMs has been presented in a multitude of studies, mainly focused on system reliability or continuity of supply and usually based on benchmarking and statistical analysis of historical performance [38–41]. A reference utility comparison can offer an *ex-ante* performance realisation tool within the framework of incentive regulation. Development of a reference utility typically relies upon a reference network model (RNM). The purpose of an RNM is to mimic an efficient but realistic network. Based on the RNM, valuable performance indicators of efficiency can be derived. RNMs have been used to gener-

ate reference investment and O&M costs as well as reliability and energy losses [124]. RNM considers spatial layout of service areas, building from scratch HV, MV and LV networks or expanding existing networks to connect new load or generation points. An alternative to this approach is to extract an RNM from a cluster of networks [125].

For energy efficiency (EE) programmes, the lost revenue can be recouped from customers with varied timing, as observed in practice [123]. A DISCO can issue a prospective surcharge, retrospective surcharge or a deferred account. With a prospective surcharge, the DISCO recovers revenue over the same time that the revenue is lost due to active EE measures. The DISCO forecasts revenue loss for the year ahead and sets a surcharge. Discrepancies between the initial forecast and verified lost revenue are reconciled in the upcoming surcharge.

The mechanism of the retrospective surcharge involves recovery of previous lost revenue. That is, the DISCO only files revenue loss for EE activities over a previous year. Reconciliation is not a major part of the process because lost revenue can be verified before the DISCO is reimbursed.

The deferred account mechanism follows all lost revenue caused by EE activities in the period between rate cases. The total lost revenue is then recovered in the next rate case as part of the DISCO's overall rate case. Prospective surcharges based on reasonably accurate EE forecasts give less cash flow variation than retrospective charges and deferred charges, which have delayed effects on revenue.

For EE programs, the main barriers to investment by a DISCO are: (1) If DISCOs are unable to recover the costs of EE programs, they will incur financial losses; (2) Unlike projects requiring capital investment, the energy efficiency solution does not produce a return over time; (3) An implicit incentive for typical DISCO businesses is that an increase in volumetric sales leads to higher profits. However, declining sales instead have the opposite effect [126].

DG programs are also faced with the above disincentives. Unless DG programs are externally funded, the administration and compensation costs must be recoverable. It is common for DISCOs to pass through these costs as surcharges. Also, independently-owned DG does not constitute an investment for a DISCO. Finally, the growth of SG

drives down energy consumption at customer sites and thus causes an erosion of the retail profit and rate base.

Worried about profitability, DISCOs in some jurisdictions are implementing mitigating measures. These include instituting capacity charges for SG, limiting SG programs based on the DISCO customer base, introducing fixed monthly charges for all customers, community partnerships, and strategic promotion of efficient load management [127]. Apart from these measures, the mitigation approaches for EE programs, such as decoupling and lost revenue adjustment mechanisms, are just as effective for SG programs [27].

In [43] DG integration and the impact of regulation on DSO operational costs are investigated. A regulation model is designed on the basis that DG integration impacts mainly distribution use of system (DUoS) charges, transmission use of system (TUoS) charges and costs of network losses. The regulation model is supported by performance analyses of regulation practice in three countries, Portugal, Denmark and Sweden. The observations made are that when net metering is in use as in Denmark and Sweden, DSOs are impacted negatively. Moreover, similar impact is seen when there is high DG penetration and a losses reward-penalty mechanism in place.

A forward-looking model to estimate several potential incentives for network investment is proposed in [44]. Given the context of incentive regulation, particularly capped revenue, the model takes the role of a DSO seeking to maximise profit. The DSO receives incentives for increasing the load factor and reducing network losses. Both of these incentives follow the well-established reward-penalty mechanism for performance evaluation. The study suggests that DSO profit can be increased with minimal overall incentive if DG is included in the network investment plan.

There are desired policy outcomes to support allocation of DG at locations that create the most value and are cheaper for society. Balanced and consistent policy interventions that avoid conflicts between issues must achieve the following [128]:

- Signals intended for DG should contain network and environmental factors;
- Power distribution costs must be minimised;

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- DSO revenues must be preserved;
- DSOs must receive incentives to integrate DG efficiently;
- Network knowledge of DSOs must be used;
- There must not be extra profits for DG owners and DSOs at the expense of society.

A notable observation is that it should be possible to send positive or negative signals to DG at the same location because incentives depend on DG penetration level. The practical implication is the need for flexible DG contracts in the future. The payment of incentives or charges can then be adjusted as the penetration level of DG changes over time.

It is suggested that DG regulation be embedded in network regulation to alleviate the information asymmetries between the DSO and regulator. This approach, however, can increase the complexity of regulation techniques.

Interaction of DG integration and network regulation. Cost plus (cost of service) regulation. Cost plus regulation does not promote efficient DG integration; particularly, the DSO is not encouraged to share cost savings of brought by DG because it decreases its revenue base. Another problem is that it is possible for the DSO to repurpose the costs of normal grid improvement as those caused by DG connections so that it gets additional revenue. In addition, the DSO has no incentive to provide site-specific signals to DG owners because it will be compensated for any costs caused by DG.

Revenue cap and price cap regulation. Concerns are raised about uncertainty of the regulator's estimations. If the regulator underestimates upcoming DG shares, the DSO may roll back on network investments to meet the disproportionate revenue cap. If the regulator overestimates DG penetration, there will be windfall profits of the DSO. The authors of [128] claim that inclusion into revenue cap or price cap regulation would be most efficient for DG integration especially for DG developers if there is price discrimination among customers.

This thesis presents models addressing DG integration with limited cost recovery and decoupling for DG-related revenue changes, and performance incentives targeting

specifically network connection of SG and IPP.

2.4 Data and Modelling Considerations

This section delineates the method employed in this thesis to characterise input time series. It further presents a summary of the market impact of RES integration, and some of the alternative tools of network operation, most of whose implementation is beyond the scope of this thesis.

2.4.1 Treatment of Input Time Series

The optimisation framework allows us to model technical complexities that arise in planning and control of power systems with RES. Demand and generation experience spatial and temporal variations. However the model can become cumbersome if the sheer size of the data and power system operational issues were to be fully considered (e.g., maintaining the power balance at every time step). RES fluctuate considerably with time even at sub-hourly rates, resulting in generation data with high granularity. Balancing the trade-offs between data detail and model complexity is an area of ongoing research [129]. Using a large amount of data typically involves other compromises such as linearising the computational model [6]. On the other hand reducing the detail in the data is one of the effective ways to keep the problem manageable. With lower dimensional data, other aspects such as network operation can be modelled with increased detail [130].

Current practice in network planning for many DISCOs involves extracting worst-case conditions out of time series and using these points instead of the entire data set [28]. The scenarios including new RES focus on ‘maximum generation–minimum load’ and ‘no generation–maximum generation’ instances. But it is recognised that more detailed representation of variability is necessary as networks become active with increasing RES [28]. A different method is that of duration curves, in which demand or generation data are arranged in proportion with time in descending order, from the highest to the lowest values. The limitation of duration curves is their inability to represent variations in demand and generation chronologically, for instance, at the

hourly scale.

A comprehensive way to represent demand or generation patterns without much manipulation is to use a large amount of available data, usually spanning one or multiple years. Annual data series have the advantage of truly capturing observed data features including short period-to-period transitions, seasonal cycles and peak conditions. But they have some disadvantages.

Although the comprehensiveness of the strategy means that it is likely to reveal relevant and unbiased detail, its application can lead to studies that are cumbersome and have computational demand. The studies may also produce results that are not much different from reconstructions that are less data intensive. Multiple studies have indeed shown that it is possible to preserve the variability of RES without enforcing a high temporal dimension [17, 129, 131]. For example, in [132] it is demonstrated that 17,502 half-hourly periods are reduced to a substantially lower total of 41 periods.

Representative day approaches extract intraday dynamics from higher dimensional data, limiting the sampled data to one or several days. A resolution of one hour intervals is reasonable though some multiyear planning studies opt for longer intervals to reduce computational complexity. Sub-hourly resolutions can be more realistic and useful especially when operating flexible resources in the growing presence of RES [133]. The scale of the representative set is often significantly less than that of the original data. Such an interpretation has appeared in a multitude of power system studies. Specific procedures range from simple heuristics to more sophisticated statistical and mathematical methods such as clustering and optimisation. Common heuristics include as a sampling four days to represent every season, each representing the first day of the season [134] and selecting days that feature extreme events [132]. A disadvantage of heuristics has been reported to be an inability to capture an events frequency of occurrence [132].

Dimension reduction of time series extends to energy storage. In a recent study, representative days are created by altering clustering algorithm weights while preserving temporal transitions, annual energy and peak conditions [129]. This approach is based on the K-medoid method. It involves picking a day with a minimised distance

between itself and other days in a shared cluster. Using different ways of representing historical data in a generation expansion model the authors examined the impact of energy storage. They found that accounting for net demand (based on individual demand and generation series) and extreme points (e.g. peak demand) in the clustering process leads to a substantial reduction of the error compared to direct clustering which is prone to understating extreme points.

Besides clustering, another effective method of devising representative profiles is optimisation. It is an approach that has not been widely reported in the research of low dimensional representation of demand or generation time series. Yet framing the problem this way allows access to a wealth of effective algorithms for finding the minimum or maximum value of a function. And the approach fits well with typical metrics informing the construction of representative profiles. Most metrics are employed to indicate the accuracy of representation.

As expected, the use of few representative periods can have increasing accuracy depending on the method of creating the representative profiles. Recent work has quantified this observation [131]. Underpinned by optimisation, the approach constructs representative daily profiles given a predefined number of days allowed to represent an annual profile. It is shown that the method reduces the representation error even when the number of representative days is limited to two. Indeed after running a generation expansion model the authors presented the cost difference between using the original annual data and the two (optimised) representative daily profiles as 0.29%.

The construction of representative periods is informed by useful criteria for assessing the accuracy of time series approximations, including representative days [131]. First, the annual load and variable generation capacity factors of the entire time series be preserved. In other words, the energy content must be closely approximated by the representative set. Second, the distribution of periods of varying generation must include high and low generation levels. Third, the correlation between different load and generation time series must be maintained. Correlation can reveal important effects such as geographical smoothing of RES. The effectiveness of correlated data is measured by comparing the correlation between representative load and generation

data with that of the original data. Fourth, short-term variability must be captured. This aspect covers dynamics such as plant ramping rates and highlights the need for flexibility. In [131] the extent of short-term variations is judged using the metric of normalised root-mean-square-error of the ramp duration curve.

The principle of representative periods not only appears in days but various other forms. Though not as prevalent as representative days, sets of hours, weeks and months have been used to extract patterns. The computational methods used to determine representative profiles are transferable to these alternative period representations. For example, an optimal selection of representative weeks can be accomplished by enumeration as demonstrated in [135]. The primary limitation of this approach is the intensive computational requirements. This means out of data spanning a year (52 weeks), tractability is limited to several weeks.

The optimisation models in this thesis can easily accept as input annual demand and generation profiles, though at noticeably greater computational time. The problem of SG and IPP allocation is difficult to solve even with modest data, due to the AC power flow constraints, disjunctions and the bilevel relationship between planning and operation. Because of the focus on modelling and its intensive requirements, the presented work makes simplifying assumptions on input data. The developed models employ representative days to capture power variations (including temporal power import/export from SG) and energy levels. A maximum of two representative profiles including worst-conditions per energy source and load are derived from a higher dimensional, annual data set. This modest representation leaves room to handle increased technical complexities in planning and operation within the same optimisation model.

2.4.2 Renewable Generation and the Wholesale Electricity Market

As the share of policy-supported RES in power systems increases competitive wholesale markets experience changing patterns in wholesale electricity pricing. Stochastic characteristics such as the occurrence of stronger winds at night (when demand is low) for wind energy and the dynamics of passing clouds in the case of solar energy, can induce price variability. Some observations are that greater generation from RES increases

the price variability in the short-run [136]. A reported consequence is that more price volatility leads to higher risk management costs as buyers attempt to mitigate price risk.

The price shifts have been noticed in different parts of the world. For example, in Germany the daytime price flattened between 2000 and 2012 [137]. Over the same period the country also experienced substantial growth in solar energy. Similar effects have been recorded in Australia, where the highest midday prices faded in 2013 relative to 2009 [138]. In California, the penetration of solar energy means that the energy price ramps up rapidly in the evening [139].

Wholesale price formation in electricity markets usually follows the merit order principle, through which a group of generators are arranged according to price, in ascending order [137, 139, 140]. The most expensive generator sets the marginal price for a given demand level. In other words the cheapest generation mix constitute the system energy supply. The composition of the group changes when variable RES are added to the mix. The near-zero marginal price of RES places them on the left side of the supply curve. As a result, for the same demand generators with the highest marginal price (before addition of RES) are displaced. And the price decreases for that period. In addition, instead of mostly fluctuating with demand only the price also changes with temporal variations in renewable energy. For accommodating new RES the effect on price implies that desirable locations could be those that provide energy during times of high prices [140]. The models developed within this thesis allow the wholesale price to be specified exogenously; any variations in price can be provided as input to the models. Therefore the models are not suitable for predicting RES-induced changes in price.

2.4.3 Alternative Methods of Network Operation

As RES become more prevalent networks offer other means of control besides DG curtailment. Network operation can be enhanced by changing the topological state of through operating tie and sectionalising switches—a method known as reconfiguration. Earliest work on reconfiguration dealt with loss reduction and feeder load balanc-

ing [141]. Since then many researchers have investigated an expanded set of objectives including minimisation of service interruption and voltage deviations. Depending on the context, some of the constraints to be satisfied are the requirements to maintain continuity of supply and radiality of the network. The problem is combinatorial because of the switching variables and sequence. A common way of solving it therefore relies on population-based, metaheuristic techniques [142]. However, there are new methods derived on the basis of continuous relaxations with promise of large-scale and real-time application [143].

Volt/var control is another mature solution for removing network constraints, usually using traditional network equipment such as on-load tap changers (OLTCs) and capacitors [144]. It continues to be improved, with DG becoming an additional source of reactive power capability. At the secondary control level it presents opportunities for optimisation by coordinating the operation of populations of OLTCs, voltage regulators, capacitors, DG units and other devices. The problem is difficult to solve because part of the control is discrete in nature while some of its constraints are not convex. Nevertheless it has been demonstrated by many researchers that volt/var control can minimise losses, voltage deviations and increase DG capacity [17, 145].

Network operators can also turn to consumers. It is widely known that using demand-side resources provides value in balancing services [146, 147]. For example, demand-side management in the form of bulk switching of thermal storage loads has been a solution for decades [148]. Recent research has focused on balancing the variable effects of RES [149]. Other emerging methods suggest the need for granular implementation to maximise DSM benefits and address the latest challenges of network operation. Using an OPF-based method makes it possible to evaluate network benefits of DSM executed at different locations [150]. The network benefits include clearing voltage and thermal constraints. Utilising demand-side resources in system operation is not without challenges. Issues such as the notion that DSM is not competitive with traditional solutions, and the lack of visibility at the distribution system level impede the uptake of DSM [151, 152].

A solution attracting considerable attention for its multiple system benefits is energy

storage. It can indeed serve many of the functions described above. Reports show that it can be coordinated with OLTCs to mitigate voltage rise in the presence variable RES [153], reduce curtailment of RES [154], provide flexible temporal capacity for DSM [155].

It is important to acknowledge that there are many aspects that can be included to make the presented models expansive and capable of providing additional value. Ideally, it should be possible to create a formulation that takes into account all realities of generation allocation. But such a formulation would lead to an intractable problem in terms of size and the type of variables and functions that it would require. So it would be impractical to solve without making assumptions that aid computation. This is one of two major reasons for this thesis does not attempt to model and solve the generation allocation problem by including all the possible realities. The second reason is that the aim of this thesis is not to aggregate all previous existing approaches. Instead the work of this thesis contributes novel SG and IPP formulations that are appropriate for practical policy and regulatory frameworks but have been neglected previously. In terms of network operation, the research narrows its focus fundamental constraints of capacity allocation before mitigating them with some strategies that have previously been demonstrated to work in related research. This is a method of modelling that has succeeded in showing the value of many approaches including DSM [150], energy loss modelling [13] and curtailment [33] in OPF.

Once fundamental value is realised, extensions can be explored to determine whether their inclusion with SG and IPP detail is of relevance and whether more complex models are major influences to the planners' decisions. For example, it is expected that exploring opportunities for energy efficiency and DSM will have implications for the DISCO's profit. Within the developed framework meeting RES goals through these mechanisms would be balanced with preserving profit and satisfying funding constraints. The work of this thesis should therefore serve as an optimal baseline for these extensions and other studies.

2.5 Summary

This chapter presented some of the main problems encountered and analysis techniques used as the presence of DG grows within power networks. It is clear from the literature review that the issues affecting SG and IPP are usually treated disparately and independently but their contexts present efficiency opportunities that are best exploited through a unified framework. Subsequent chapters synthesise the concepts from regulation, and network planning and operation to optimally allocate DG based on more concrete perspectives of decision-makers.

Chapter 3

Renewable Generation Hosting Capacity Allocation

3.1 Introduction

This chapter introduces the preliminary models underpinning DG integration and regulation optimisation models presented later in the thesis. First the fundamental OPF problem to determine power flows on constrained networks is presented. A simple rule of RES capacity allocation is established and applied to the solution of OPF. While this approach produces technically compliant SG and IPP sets, it lacks a clear facility to decide the best option for profit maximisation out of numerous valid sets. This motivates the development of a more principled method, which defines explicitly the DISCO's motive and its environment. The resulting optimisation models provide SG and IPP allocations that maximise profit for the DISCO in an environment promoting RES growth.

3.2 Hosting Capacity Allocation Models

3.2.1 AC Optimal Power Flow

The standard OPF is typically described as a generalised optimisation problem in the following form:

$$\underset{u,x}{\text{minimise}} \quad f(u,x), \quad (3.1a)$$

$$\text{subject to} \quad g(u,x) = 0, \quad (3.1b)$$

$$h(u,x) \leq 0. \quad (3.1c)$$

The objective function $f(u,x)$ poses the aim of the optimisation. Equality and inequality constraints are represented by $g(u,x)$ and $h(u,x)$; control variables are designated the vector u and state variables, the vector x . The complexity of the OPF problem varies considerably depending on the selection and treatment of functions f , g and h as well as whether the variables are continuous, discrete or mixed. The objective function of the standard OPF is the minimised sum of active power generation costs,

$$\underset{u,x}{\text{minimise}} \quad \sum_{i \in \Omega_I} \sum_{e \in \Omega_E} c_{(n_E-e)} P_i^{n_E-e}, \quad (3.2)$$

which is composed of polynomial functions, where the index e and maximum index n_E in the set Ω_E , combine to give the cost coefficient index and powers of active power P_i for a generator set Ω_I . For instance, a single generator with a quadratic cost function $\Omega_I = \{1\}$, $n_E = 2$, $\Omega_E = \{0, 1, 2\}$, forms the objective function, $c_2 P_1^2 + c_1 P_1 + c_0$. Reactive power costs can also be expressed in the same manner. For conventional generation, the objective function represents fuel costs; for RES, it defines the cost of curtailment or generator priority. In addition to generator active power and reactive power, the vector of optimisation variables contains the bus voltage magnitudes and angles. The equality constraints denote the nodal real and reactive power balance. The basis of the power flow formulations in this thesis is the bus injection model, which expresses the complex power variables, P and Q , as functions of voltage phasors,

\hat{V} and their conjugates, \hat{V}^* [156, 157]: the voltage and current phasors have a linear relationship,

$$\hat{I}_d = \sum_{j \in D} \hat{Y}_{dj} \hat{V}_j, \quad (3.3)$$

the complex power is a nonlinear function of the voltage and current phasors,

$$P_d + jQ_d = \hat{V}_d \hat{I}_d^*, \quad (3.4)$$

the current phasor is substituted using (3.3) to give the complex power and voltage phasor relation,

$$P_d + jQ_d = \hat{V}_d \sum_{j \in D} \hat{Y}_{dj}^* \hat{V}_j^*. \quad (3.5)$$

where \hat{I}_d is the current injection phasor and \hat{Y}_{dj} is the given branch admittance, which is an element in the admittance matrix. The admittance matrix is constructed based on the network topology and a π -model for lines and transformers, as detailed in [158] and power systems textbooks including Chapter 7 of [157]. The inequality constraints are composed of allowable operating voltage range, thermal branch flow limits and power generation limits.

3.2.2 Interior-Point Method

To achieve operational feasibility, formulations proposed in this thesis embed the exact nonlinear OPF problem, i.e., using real-valued representation of (3.5) as opposed as opposed to more computationally amenable but less precise linear or convex formulations. The nonlinear program is then solved using the primal-dual interior-point method, described in [159]. Although there are other algorithms that can solve nonlinear programs (such as sequential quadratic programming [98, 160, 161]), the focus herein is restricted to interior-point methods. This choice is motivated by the demonstrated success of these methods. Interior-point methods have indeed gained wide acceptance for their effectiveness when solving large-scale NLP problems, including OPF [162–164]. Their advantages include speed of convergence and the ability to handle inequality constraints with ease. These methods have a rich history in broad OPF research beginning with

early advances inspired by the pioneering study of interior point methods in linear programming [165, 166]. Variants of OPF solved with these methods are also found in commercial applications [167].

The rest of this section provides details of the basic interior-point method. This method finds the local minimum of a constrained optimisation problem. It can handle linear, nonlinear, convex and non-convex objective and constraint functions as long as they are once and ideally twice continuously differentiable. By employing a logarithmic barrier function, the interior-point method accommodates inequality constraints. Another key feature of the method is the newton step that searches for a point that satisfies a set of necessary conditions. Given the problem in (3.1), the inequality constraint can be removed, culminating in the following canonical transformation (u is dropped for conciseness):

$$\underset{x,s}{\text{minimise}} \quad f(x), \quad (3.6a)$$

$$\text{subject to} \quad g(x) = 0, \quad (3.6b)$$

$$h(x) - s = 0, \quad (3.6c)$$

$$s \geq 0. \quad (3.6d)$$

The nonnegative slack variable s transforms the inequality constraint $h(x) \leq 0$ into an equality constraint. Next, the interpretation of the method with a barrier term is described [98].

$$\underset{x,s}{\text{minimise}} \quad f(x) + \mu \sum_{v \in M_s} \ln s_v, \quad (3.7a)$$

$$\text{subject to} \quad g(x) = 0, \quad (3.7b)$$

$$h(x) - s = 0. \quad (3.7c)$$

where μ is a positive parameter; v and M_s denotes the index and set of inequality constraints. The solution of (3.7) approaches that of (3.6) as μ nears zero. For a solution to produce a local minimum of the problem, a set of equations called the first

order necessary conditions must be satisfied. The first order conditions, also known as the Karush-Kuhn-Tucker (KKT) conditions, involve the first derivatives of the objective and constraint functions. Before the conditions are stated, the Lagrangian function of the problem (3.7) must be defined:

$$\mathcal{L}(x, s, y, z) = f(x) - y^\top g(x) - z^\top (h(x) - s), \quad (3.8)$$

where y and z are the Lagrange multipliers. The KKT conditions for the equality constrained nonlinear program (3.7) are obtained by taking the partial derivatives of the Lagrangian function (3.8) with respect to each of the variables x, s, y, z and setting them to zero. Indeed the KKT conditions are given by (3.9).

$$\nabla f(x) - A_g^\top(x)y - A_h^\top(x)z = 0, \quad (3.9a)$$

$$z - \mu S^{-1}e = 0, \quad (3.9b)$$

$$g(x) = 0, \quad (3.9c)$$

$$h(x) - s = 0, \quad (3.9d)$$

the rational equation (3.9c) is transformed into the more amenable quadratic equation (3.10)

$$Sz - \mu e = 0, \quad (3.10)$$

where $A_g(x)$ is the Jacobian of $g(x)$; $A_h(x)$ is the Jacobian of $h(x)$; S is a diagonal matrix of slack variables, and $e = (1, 1, \dots, 1)^\top$. Newton's method is applied to solve the KKT equations. The Newton step finds a vector p^r that minimises the Taylor series approximation (based only on first derivative terms) of (3.9). Suppose r represents the functions in (3.9) and A_r is the Jacobian of r , then the newton equations at every iteration take the following linear form,

$$A_r p_r = -r. \quad (3.11)$$

The more explicit matrix representation of the Newton step is written as

$$\begin{bmatrix} \nabla_{xx}^2 \mathcal{L} & 0 & -A_g^\top(x) & A_h^\top(x) \\ 0 & Z & 0 & S \\ A_g(x) & 0 & 0 & 0 \\ A_h(x) & -I & 0 & 0 \end{bmatrix} \begin{bmatrix} p_x \\ p_s \\ p_y \\ p_z \end{bmatrix} = - \begin{bmatrix} \nabla f(x) - A_g^\top(x)y - A_h^\top(x)z \\ Sz - \mu e \\ g(x) \\ h(x) - s \end{bmatrix} \quad (3.12)$$

where I denotes the identity matrix and $\mathcal{L}(x, s, y, z)$ refers to the Lagrangian for (3.6a)–(3.6c). The above step obtains the primal-dual search direction (p_x, p_s, p_y, p_z) . Then the subsequent iteration provides (x^+, s^+, y^+, z^+) based on¹

$$x^+ = x + \alpha_s^{\max} p_x, \quad (3.13a)$$

$$s^+ = s + \alpha_s^{\max} p_s, \quad (3.13b)$$

$$y^+ = y + \alpha_z^{\max} p_y, \quad (3.13c)$$

$$z^+ = z + \alpha_z^{\max} p_z. \quad (3.13d)$$

The step lengths α_s^{\max} and α_z^{\max} are updated such that s and z are prevented from quickly reaching zero:

$$\alpha_s^{\max} = \max\{\alpha \in [0, 1] : s + \alpha p_s \geq (1 - \tau_p)s\}, \quad (3.14a)$$

$$\alpha_z^{\max} = \max\{\alpha \in [0, 1] : z + \alpha p_z \geq (1 - \tau_p)z\}, \quad (3.14b)$$

The value of τ_p lies between 0 and 1, with a typical value of 0.995. An error function is defined to track convergence after every iteration,

$$E_{cn}(x, s, y, z; \mu) = \max\{\|\nabla f(x) - A_g^\top(x)y - A_h^\top(x)z\|, \|Sz - \mu e\|, \|g(x)\|, \|h(x) - s\|\} \quad (3.15)$$

where $\|\cdot\|$ denotes the norm of a vector.

For a more detailed treatment of interior-point methods, the interested reader is referred to [98]. The underlying OPF problems in subsequent chapters are formulated

¹The compact style here is meant to be equivalent to the notation: $x^{k+1} \leftarrow x^k + \alpha_s^{\max} p_x^k$ where k is the iteration count.

Algorithm Overview Basic Interior-Point Method

- Step 0.** Select initial values of x and s ($x_0, s_0 > 0$). Calculate the values of multipliers y_0 and z_0 .
Choose an initial barrier parameter $\mu > 0$ and parameters $\sigma, \tau_p \in (0, 1)$.
Set $k = 0$.
- Step 1.** Solve (3.12) to obtain the primal-dual search direction (p_x, p_s, p_y, p_z) .
- Step 2.** Compute the step lengths α_s^{\max} and α_z^{\max} .
- Step 3.** Update the solution $x^{k+1}, s^{k+1}, y^{k+1}, z^{k+1}$ using (3.13).
- Step 4.** Convergence criteria. $E_{cn}(x, s, y, z; \mu) \leq \mu_k$. In general, iterations terminate whenever primal feasibility, dual feasibility and optimality conditions are satisfied.
- Step 5.** If convergence is not achieved, go to Step 6, otherwise stop.
- Step 6.** Update barrier parameter $\mu_k \in (0, \sigma\mu_k)$; $k = k + 1$.
-

to suit the algorithm by Wang *et al.* [159], which is an instance of the above method with modified convergence criteria. The algorithm is implemented in Matpower [158].

3.3 Case Study: 14-bus System

The first part of this section deals with the capacity integration using a multi-period OPF model. The multi-period OPF solves a polynomial cost function subject to the operating constraints and variable demand and generation. It optimally dispatches generators of a specified size within their lower and upper limits. The multi-period OPF model is applied to the 14-bus system shown in Fig. 3.1 and detailed in Tables 3.1–3.3. Additional input data for demand and generation, including daily profiles, are given in Appendix A. Wind is the energy resource utilised for all the DGs in the system. Bus-3 and bus-10 represent the candidate buses DG connections. The voltage at each bus in the distribution system is expected to be within the range $\pm 5\%$ of the nominal voltage. The maximum capacity for a single SG must be lower than 5 MW, which is the minimum value for an IPP. This value can be adjusted according to requirements faced by the generators. Several scenarios of OPF allocation are constructed in order to quantify its performance.

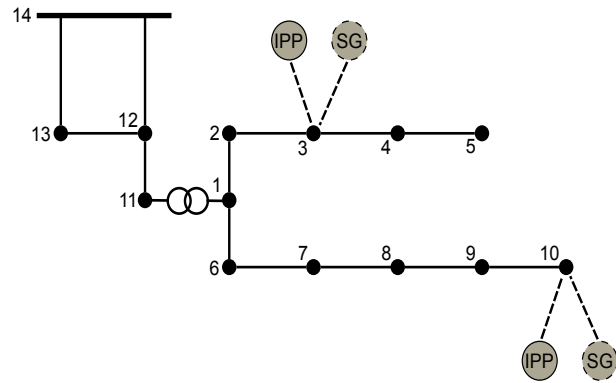


Figure 3.1: The 14-bus distribution system with candidate connection points for IPPs and SGs.

Table 3.1: Bus Data

| Bus Number | Bus Type | Load |
|------------|----------|----------------|
| 1-10 | PQ | 1.4 MVA (Base) |
| 12 | PQ | 22 MW, 0.95 pf |
| 13 | PQ | 18 MW, 0.95 pf |
| 14 | Slack | - |

Table 3.2: Lines Data

| Bus (From) | Bus (To) | x (Ω/km) | r (Ω/km) | Length (km) |
|------------|----------|----------------------------|----------------------------|-------------|
| 1 | 2 | 0.35 | 0.12 | 1.2 |
| 2 | 3 | 0.35 | 0.12 | 1.2 |
| 3 | 4 | 0.35 | 0.12 | 1.2 |
| 4 | 5 | 0.35 | 0.12 | 1.2 |
| 1 | 6 | 0.35 | 0.12 | 1 |
| 6 | 7 | 0.35 | 0.12 | 1 |
| 7 | 8 | 0.35 | 0.12 | 1 |
| 8 | 9 | 0.35 | 0.12 | 1 |
| 9 | 10 | 0.35 | 0.12 | 1 |
| 14 | 12 | 0.5 | 0.15 | 16 |
| 14 | 13 | 0.5 | 0.15 | 9 |
| 13 | 12 | 0.5 | 0.15 | 8 |
| 12 | 11 | 0.5 | 0.15 | 10 |

Table 3.3: Transformer Data

| Bus (From) | Bus (To) | Voltage Levels (kV) | Capacity (MVA) | x (pu) | r (pu) | OLTC |
|------------|----------|---------------------|----------------|----------|----------|------------------------|
| 11 | 1 | 70/10 | 18 | 0.12 | 0.012 | -10% to 10% (16 Steps) |

3.4 Results and Discussion: OPF Allocation Model

This section demonstrates the impact of renewable DG on network operation and how network capacity can potentially be shared among DG candidates on the 14-bus system. Reverse power flow is emphasised for its various technical impacts. Known issues include the risk of failure of protection systems. Some protection systems are coordinated and graded with the assumption that there will only be one way power flow. When the direction of the power flow is reversed, protection may fail to operate as expected [168]. In other cases, energy overflow may be an issue. There may not be sufficient external network demand, which can lead to curtailment or displacement of external generation.

The reverse power constraint is enforced in standard OPF by setting the lower limit of external grid generation to an amount that provides zero flow from the lower voltage side to the higher voltage side of the transformer in Fig. 3.1. The disadvantage of this method is that the minimum generation figure has to be known in advance. To overcome this, the OPF formulation must be modified to include an explicit flow constraint for transformers.

The reverse power constraint has a limiting effect on DG capacity. Beyond the total capacity of 12 MW (6 MW at bus-3 and bus-10), power flows to the higher voltage side of the transformer. However, this flow can be reduced to zero if curtailment of generation is permitted.

The curves in display in Fig. 3.2 represent the total daily losses. Losses vary with DG capacity, mainly declining from the load-only case to the lowest point, with connected DG accounting for 12 MW. After that point, losses on the lower voltage side of the transformer start increasing. On the higher voltage side the losses carry on the declining trend. By not imposing a power flow constraint on the transformer, the energy losses on the lower voltage side ultimately increase with capacity. Losses are maintained near the minimum when the constraint is active, see Fig. 3.3. That is when capacity is allowed to grow but curtailment is put into effect. Suppose a zero RPF limit is imposed and curtailment is not allowed. It is clear from Fig. 3.4 that if local generation is attached and limited according to local demand levels, some capacity allocations will not be

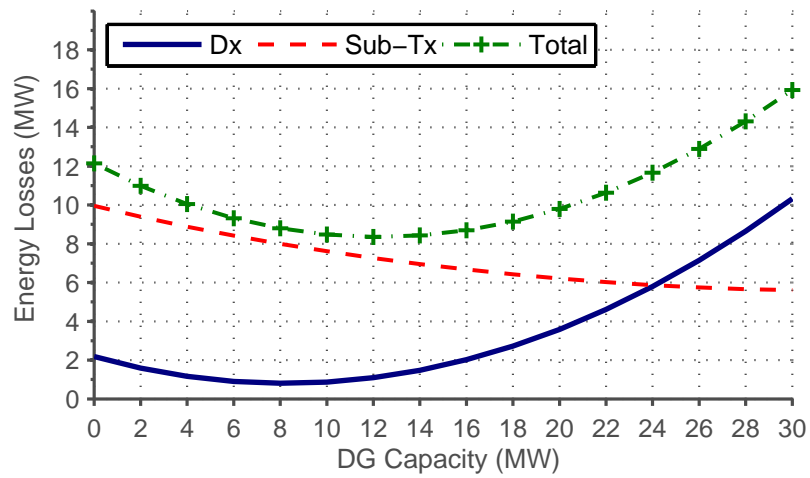


Figure 3.2: Breakdown of energy losses as a function of the total DG capacity in the absence of an RPF limit. Dx: network on the lower voltage side of the transformer between bus-11 and bus-1. Sub-Tx: network on the higher voltage side of the transformer.

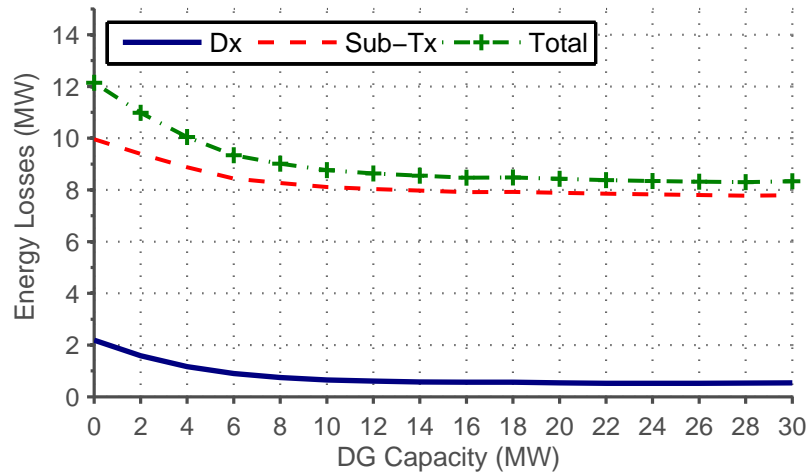


Figure 3.3: Breakdown of energy losses in the presence of the RPF limit.

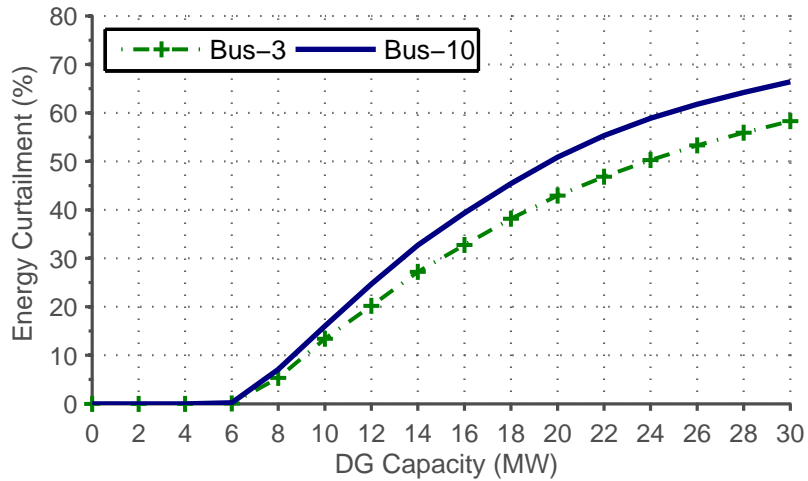


Figure 3.4: Curtailed energy under binding constraints and capacity growth.

feasible. When the network capacity is meant to be shared by SG and IPP, further allocation will be necessary. For instance, deploying DG producing 79% of the local energy demand at bus-3 takes up 2 MW (Fig. 3.5). Simultaneously deploying IPP with a minimum size of 5 MW would raise the capacity set aside to 7 MW, creating a 1 MW deficit from the OPF figure of 6 MW. The same problem occurs at bus-10. Another significant observation relates to curtailment of SG. Referring to Fig. 3.6, there are times during which generation curtailment is necessary. The amount of power curtailed is in response to network constraint violations. This presents a problem when generation is intended to meet local demand. Intuitively, local generation must only be curtailed when it exceeds local demand. At maximum curtailment, local generation must be level with local demand. So far, the DG capacity can be determined but remains unallocated within OPF in terms of DG class, namely, SG and IPP. Given the total capacity of 12 MW calculated by OPF, it is possible to distribute to each candidate bus SG and IPP. An example rule that is easy to follow could be: limit SG energy per bus equal to a portion (less than 100%) of local energy demand and allow IPP to take up the remaining capacity. Suppose as a result SG makes up 79% of the local load. This amounts to 2 MW of SG capacity per bus. This rule can be maintained as long as the IPP does not violate its allowable lower bound (5 MW). Table 3.4 compares the resulting permutations of SG and IPP bus capacity. The allocations

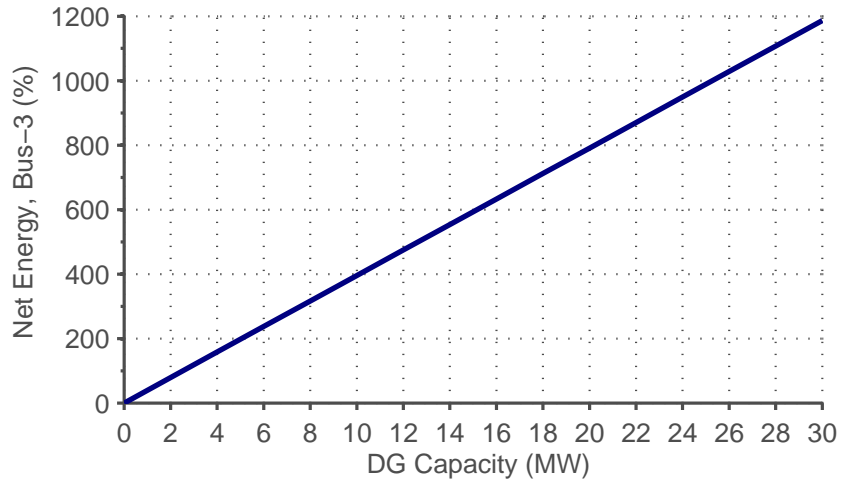


Figure 3.5: Local net energy with and without the RPF limit.

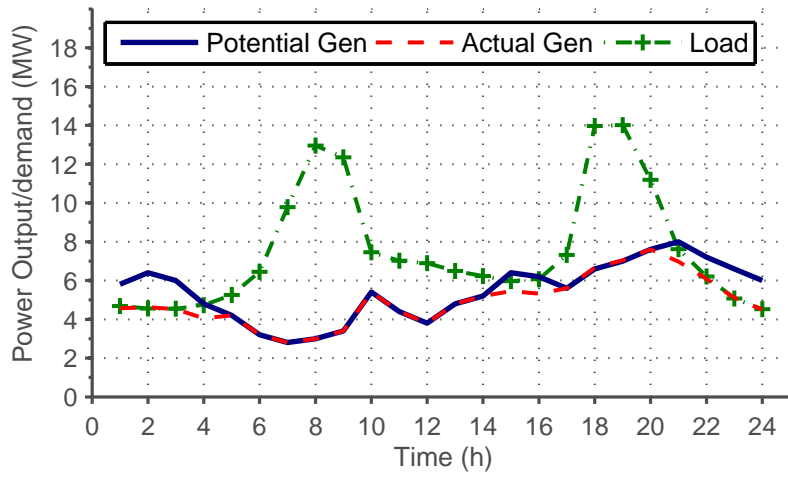


Figure 3.6: Local net energy with and without the RPF limit.

differ by DG type proportions and enabled total capacity. Two permutations stand out; the SG only case, which produces the lowest capacity, and the IPP only case, which results in significantly higher capacity of 12 MW. The question arising with use

Table 3.4: Alternative SG-IPP capacity allocations

| Bus-3 | | Bus-10 | | System |
|---------|----------|---------|----------|------------|
| SG (MW) | IPP (MW) | SG (MW) | IPP (MW) | Total (MW) |
| 0 | 0 | 0 | 0 | 0 |
| 0 | 6 | 0 | 6 | 12 |
| 0 | 6 | 2 | 0 | 8 |
| 2 | 0 | 0 | 6 | 8 |
| 2 | 0 | 2 | 0 | 4 |

of the rule-based OPF capacity allocation approach has to do with the distribution of capacity at the candidate locations. Based on considerations that drive DISCO decisions, is there an effective way to determine the capacity and location of DG in the form of SG and IPP? The next section establishes criteria for deciding between possible capacity determinations, particularly describing the mathematical formulation and demonstrating the numerical results of a DISCO-focused model to allocate SG and IPP.

3.5 DG Cost and Benefit Formulation

In the absence of DGs the DISCO purchases bulk supply of energy from the wholesale market. The unit price of wholesale energy is C^W . In the event of a renewable IPP connection, the same price applies but a distinction is drawn from other generator types by an additional payment for RECs, which is denoted by C^{rc} .

Whenever SGs receive energy from the distribution system, a retail unit price C^r is applied by the DISCO. The total amount paid to the DISCO depends on the state of generation because SGs can simultaneously generate and receive energy. For each unit of energy generated locally, SGs charge C^G . Supply from the system is fully

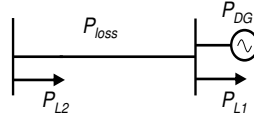


Figure 3.7: 2-bus system.

displaced when generated energy exceeds local supply. The residual is exported to the distribution system at a unit price C^{et} .

Implications of SG integration. The following expressions describe the expected profit Y_p when a load $P_{L,2}$, is supplied by a DG (P_{DG}) for cases when the DISCO receives energy exported at bus 2 at no cost. Such cases offer a way to offset the effects of income erosion. The term SG denotes the coupling of $P_{L,2}$ and P_{DG} .

1. SG importing energy ($P_{L,2} - P_{DG} \geq 0$):

$$Y_p = C^r(P_{L,1} + P_{L,2} - P_{DG})\tau - C^W(P_{L,1} + P_{\text{loss}} + P_{L,2} - P_{DG})\tau$$

$$Y_p = (C^r - C^W)(P_{L,1} + P_{L,2} - P_{DG})\tau - C^W P_{\text{loss}}\tau \quad (3.16)$$

2. SG exporting energy ($P_{L,2} - P_{DG} \leq 0$):

$$Y_p = C^r P_{L,1}\tau - C^W(P_{L,1} + P_{\text{loss}} + P_{L,2} - P_{DG})\tau$$

$$Y_p = (C^r - C^W)(P_{L,1})\tau + C^W(P_{DG} - P_{\text{loss}} - P_{L,2})\tau \quad (3.17)$$

DGs, in general, reduce network losses by supplying local demand and thus decreasing the overall network demand. Energy cost savings represent the financial benefit for the DISCO since less energy is purchased from upstream sources. From (3.16) and (3.17) it can be seen that reducing losses raises the DISCO profit. While this function is a positive attribute for SGs, increasing power output has a significant and undesirable effect; energy sales decrease as production from the SG increases. In event of excess production from the SG, the DISCO only receives retail payment from the load at bus 1. However, there is also an opportunity to acquire SG energy at no cost. Energy exported by the SG decreases the wholesale electricity cost. Raising exported

energy can create a net benefit for the DISCO because the lower limit for retailed energy is zero for all export levels.

SGs can also be employed to assist with RES quota compliance. When SG energy production is considered, the quota decreases from $r_o \times (\text{Total load})$ to $r_o \times (\text{Total load} - P_{DG})$, thereby reducing the obligation costs [169].

Implications of IPP integration. Like SGs, IPPs reduce losses by producing energy to meet local demand; but that is where the similarity ends. For an IPP to be connected there needs to be sufficient network capacity to accommodate the minimum allowable plant size. Financial benefits are observed when the IPPs are integrated into distribution networks to comply with a quota obligation. In this regard, the DISCO must reach a certain level of IPP connections to achieve compliance or pay a penalty fee for the shortfall. Therefore the DISCO avoids penalty costs with the connection of IPPs.

The usual step during calculation of DG hosting capacity is to select the most representative scenarios that ensure constraint violations are avoided. That is the extreme low demand - high supply scenario. A multi-period approach is appropriate in this study as it provides better estimation of variable demand and supply scenarios that especially influence the costs and benefits of SGs.

3.6 RES Allocation Model: *Problem 1*

The RA expects the DISCO to connect any RES seeking connection to the network, and allows the RES support costs to be passed through to ratepayers. The DISCO may not recover lost revenue but may benefit from the energy exported from the SG. The RA specifies the target for energy generation from IPPs and the allowable budget for the FiT support scheme for a future period, which in this study is one year. With these values, the combined cost of quota obligation and FiT support schemes can be estimated.

The financial benefit for IPPs lies in the income from energy production. SGs benefit from cost savings due to the reduction of energy consumption and income from energy production. The implementation and extent of compensation varies widely. Mainly,

the income source can take the form of net metering or payments for energy produced and energy exported. The latter approach is employed in the proposed formulation. For energy generation, the SG is rewarded for all energy produced at the facility. An additional payment is made to the SG for surplus energy that is supplied to the distribution network.

The DISCO can exercise several options to meet the quota obligation. One possibility is to only make payments and not connect any IPPs. Another potential decision is to combine IPP connections and alternative payments. Lastly, the DISCO may fulfil the full quota through IPP integration. These decisions are realised by employing (3.19). The status of quota compliance is represented by the variable u_c . When the DISCO complies with the quota obligation, it only incurs the cost of wholesale electricity. If the DISCO fails to fill the IPP quota the total cost becomes the sum of alternative payments and wholesale cost. The first two terms in (3.21) represent income from energy retailing. The first term represents a loss of revenue due to a decrease in energy consumption when SGs are introduced. The middle term is revenue from all consumers. The last term is the cost of bulk energy purchased at the wholesale price. As expected, when local generation is zero at any SG site true demand is unmasked and the DISCO receives full income just like at other pure load buses. Once the SG capacity rises to levels whereby generation exceeds demand, a saving in wholesale electricity is realised. Note that because self-generation is financed by power users, the DISCO only serves as an intermediary. Hence the cost of SG production is not included as part of the profit function. The sum of the quota obligation and profit functions form the objective function that enables distribution of generation capacity between IPPs and SGs. The full mathematical formulation is presented as follows:

Problem 1: RES location and capacity allocation

$$\text{minimise } J_Q + J_D, \quad (3.18)$$

$$J_Q = \left(C^b \sum_{t \in T} \left(r^o \sum_{d \in D} P_{L,d}^t - \sum_{i \in I} P_{IPP,i}^t \right) \tau \right) u_c, \quad (3.19)$$

$$u_c = \text{sgn}^+ \left(\sum_{t \in T} \left(r^o \sum_{d \in D} P_{L,d}^t - \sum_{i \in I} P_{\text{IPP},i}^t \right) \tau \right). \quad (3.20)$$

$$\begin{aligned} J_D = C^r \sum_{i \in N} \sum_{k \in K} P_{k,t}^E \tau - C^r \sum_{t \in T} \sum_{d \in D} P_{L,d}^t \tau \\ + C^e \sum_{t \in T} (P_s^t + \sum_{i \in I} P_{\text{IPP},i}^t) \tau, \end{aligned} \quad (3.21)$$

Constraints:

1. Net energy limit:

$$\sum_{t \in T} \sum_{k \in K} (P_{\text{SG},k}^t - P_{\text{SGL},k}^t) \geq 0, \quad (3.22)$$

2. Power-flow balance at the i th interval:

$$\begin{aligned} P_{G,d}^t - P_{L,d}^t = V_d^t \sum_{j=1}^D V_j^t [G_{dj}^t \cos(\delta_d^t - \delta_j^t) \\ + B_{dj}^t \sin(\delta_d^t - \delta_j^t)], \end{aligned} \quad (3.23)$$

$$\begin{aligned} Q_{G,d}^t - Q_{L,d}^t = V_d^t \sum_{j=1}^D V_j^t [G_{dj}^t \sin(\delta_d^t - \delta_j^t) \\ - B_{dj}^t \cos(\delta_d^t - \delta_j^t)]. \end{aligned} \quad (3.24)$$

3. Bus voltage limits:

$$V^{\min} \leq V_d^t \leq V^{\max}. \quad (3.25)$$

4. SG capacity:

$$0 \leq G_{\text{SG},k} \leq G_{\text{SG},k}^{\max}. \quad (3.26)$$

5. IPP capacity:

$$u_{\text{IPP},i} G_{\text{IPP}}^{\min} \leq G_{\text{IPP},i} \leq u_{\text{IPP},i} G_{\text{IPP}}^{\max}, \quad u_{\text{IPP},i} \in \{0, 1\}. \quad (3.27)$$

6. Thermal loading limit:

$$(P_{d,j}^{t^2} + Q_{d,j}^{t^2})^{1/2} \leq S_{d,j}^{\max}. \quad (3.28)$$

7. System net power flow:

$$P_s^t \geq 0. \quad (3.29)$$

The total energy produced by the SG must not exceed local energy demand over the evaluation period. $P_{k,t}^E = P_{SGL,k}^t - P_{SG,k}^t$ if $P_{SG,k}^t \leq P_{SGL,k}^t$ and $P_{k,t}^E = 0$ otherwise. The voltage at each bus must be maintained within the appropriate range at all times. The total power consumption must be equal to the total power supply at each bus. SG and IPP capacity must be in the permitted range. The disjunctive IPP capacity constraint (3.27) stems from the differentiating rule for SG and IPP. The lowest allowable capacity for an IPP must be higher than the upper limit for an SG. Therefore, no single DG unit can be categorised as both an SG and an IPP. Thermal loading of lines and transformers must be less or equal to than the levels derived from manufacturer ratings. The power flow at the distribution substation must not be negative, meaning the distribution system must not export power upstream over any time interval. Note that this constraint can be adapted in line with the capability of the network. Next, an algorithm employed to solve the proposed optimisation model is described.

3.7 Allocation Algorithm

There exists different algorithms for solving the DG location and capacity problem, mostly in the realms of classical, exact techniques, and population-based techniques. Both approaches are applied in tandem in the present work—the IPM is combined with PSO to ultimately solve a non-convex, nonlinear, bilevel problem. But first this section presents an application of PSO to numerically solve *Problem 1*.

There are several advantages to using PSO to solve optimisation problems. The algorithm is flexible and easily adaptable to the special characteristics of the mathematical model. Unlike classical optimisation algorithms PSO is not restrictive in terms of the objective function; that is, the function does not have to be convex, differen-

tiable or continuous to be solved with the algorithm. Due to its stochastic nature the algorithm is able to escape local solutions and reach global optima. The initialisation of PSO involves a set of arbitrary solutions, relaxing the requirement for a high quality initial solution. Compared to other population-based approaches, the algorithm is simple to implement, converges fast [170], and only requires adjustment of a few parameters. PSO has been applied with success to power systems. Examples include optimal power flow [171] and transmission network planning [172].

PSO simulates the social behaviour of a flock of birds in flight. Potential solutions are represented by groups of individuals referred to as particles. A particle relies on personal information and that available in its neighbourhood as it progresses along a search path. The particle's movement is directed by its velocity. This information enables the particle to improve its position and move towards optimum solutions [173, 174].

As particles move in a multidimensional search space, the position of particle p is denoted by \mathbf{x}_p^{k+1} and calculated as the sum of the previous position, \mathbf{x}_p^k and velocity, \mathbf{v}_p^{k+1} :

$$\mathbf{x}_p^{k+1} = \mathbf{x}_p^k + \mathbf{v}_p^{k+1}. \quad (3.30)$$

The individual and social experiences are shared and embedded in the velocity term, which steers the particle from one position to another. There are two different processes through which a particle accumulates experience. It can either learn the best location encountered by the swarm or population as a whole, or limit its social interaction to a smaller group within the population. The former is called global best PSO and the latter local best PSO.

For global best PSO, the particle velocity is updated using

$$\mathbf{v}_p^{k+1} = w\mathbf{v}_p^k + c_1r_1(\mathbf{y}_p^k - \mathbf{x}_p^k) + c_2r_2(\mathbf{y}_g^k - \mathbf{x}_p^k), \quad (3.31)$$

where \mathbf{y}_p^k is the best position of particle p , \mathbf{y}_g^k is the best position in the particle population, c_1 and c_2 are acceleration constants, and r_1 and r_2 are defined as two uniformly distributed random numbers in $[0, 1]$.

The velocity update is the sum of the previous velocity, social and cognitive components. The previous velocity \mathbf{v}_p^k preserves particle experience in the immediate past; the cognitive component $c_1 r_1 (\mathbf{y}_p^k - \mathbf{x}_p^k)$ represents the tendency of the particle to maintain previous best performance; the social component $c_2 r_2 (\mathbf{y}_g^k - \mathbf{x}_p^k)$ quantifies the performance of the particle with reference to its neighbours.

Exploration and exploitation are the two significant characteristics of the velocity update [173]. The algorithm can find a good optimum by exploring different areas of the search space —this capability is known as exploration. Exploitation refers to the capability of the algorithm to focus the search on a region that is likely to improve an existing solution. In order to achieve a balance between the two characteristics, particle movement has to be regulated. The values of velocity \mathbf{v}_p^k must fall within $[v^{\min}, v^{\max}]$. A clamping mechanism is implemented to ensure the requirement is satisfied before the particle position is updated. When $\mathbf{v}_p^k < v^{\min}$, the velocity is adjusted to $\mathbf{v}_p^k = v^{\min}$. For the opposite case whereby $\mathbf{v}_p^k > v^{\max}$, the velocity is set to $\mathbf{v}_p^k = v^{\max}$. This prevents the velocity from overshooting desired values. The mechanism is fully described by (3.32).

$$\mathbf{v}_p^k = \begin{cases} v^{\max}, & \text{if } \mathbf{v}_p^k > v^{\max}; \\ \mathbf{v}_p^k, & \text{if } v^{\max} \leq \mathbf{v}_p^k \leq v^{\max}; \\ v^{\min}, & \text{if } \mathbf{v}_p^k < v^{\min}. \end{cases} \quad (3.32)$$

Like the velocity, the particle position is also bounded using (3.33).

$$\mathbf{x}_p^k = \begin{cases} x^{\max}, & \text{if } \mathbf{x}_p^k > x^{\max}; \\ \mathbf{x}_p^k, & \text{if } x^{\min} \leq \mathbf{x}_p^k \leq x^{\max}; \\ x^{\min}, & \text{if } \mathbf{x}_p^k < x^{\min}. \end{cases} \quad (3.33)$$

All particles are randomly initialised as follows:

$$\mathbf{x}_p^0 = \lceil x^{\min} + \mathbf{rand}_p(x^{\min} - x^{\max}) \rceil. \quad (3.34)$$

$$\mathbf{y}_p^{k+1} = \arg \min_{\mathbf{x}_p^k: 0 \leq p \leq k} \{f(\mathbf{x}_p^k)\} \quad \forall p = 1, \dots, N_p \quad (3.35)$$

In minimisation problems, the best position along a search path is determined according to (3.36)

$$\mathbf{y}_p^{k+1} = \begin{cases} \mathbf{y}_p^k, & \text{if } f(\mathbf{x}_p^{k+1}) \geq f(\mathbf{y}_g^k); \\ \mathbf{x}_p^{k+1}, & \text{if } f(\mathbf{x}_p^{k+1}) < f(\mathbf{y}_g^k); \end{cases} \quad (3.36)$$

where $f(\mathbf{x}_p^{k+1})$ is the fitness function, which is a measure of performance, indicating the quality of the solution in relation to the optimum. The global best position in the k th step is selected among the particle best solutions and is given by \mathbf{y}_g^k when

$$f(\mathbf{y}_g^k) = \min\{f(\mathbf{y}_0^k), \dots, f(\mathbf{y}_p^k), \dots, f(\mathbf{y}_{N_p}^k)\}, \quad (3.37)$$

where N_p is the size of the swarm, i.e., the total number of particles.

For local best PSO, the swarm is segmented into smaller groups. neighbourhood arrangements

$$f(\mathbf{y}_{gz}^k) = \min\{f(\mathbf{y}_{0z}^k), \dots, f(\mathbf{y}_{pz}^k), \dots, f(\mathbf{y}_{N_pz}^k)\}, \quad (3.38)$$

The two forms of PSO are especially different in terms of convergence and diversity. Through wider interaction between particles, global PSO is able to converge faster than local best PSO. However, this leaves parts of the search space uncovered. In contrast, local best PSO provides more diversity through neighbourhood segmentation. Thus, it is less likely to be trapped in locally optimal regions.

Constraints are addressed within the algorithm by introducing a penalty term, as in (3.39). The penalty coefficient p is assigned a high value to penalise violation of constraints. As such, the fitness function increases as solutions become infeasible and vice versa.

$$J + p \sum_{u=1}^M \max(0, h_u). \quad (3.39)$$

Logical relationships are constructed with a heuristic constraint technique. The technique maintains feasibility of the constraints, thereby avoiding frequent violations and

Table 3.5: PSO parameters

| Parameter Name | Parameter Value |
|--|--------------------------------|
| Number of iterations | 200 |
| Population | 8 |
| Inertia (w) | $0.5 + \frac{1}{2(\ln k + 1)}$ |
| Acceleration constants (c_1, c_2) | 2 |
| Velocity limits ($v^{\min} = -v^{\max}$) | $0.25x_p$ |
| Penalty coefficient (p) | 500 |

improving the quality of the solutions [175]. Parameters of the algorithm are set to values listed in Table 3.5. The iteration limit and particle population have been selected after observing no major change in the solution when the values are increased. The inertia, acceleration constants and velocity limits are based on typical values in the literature. The penalty coefficient is obtained by trial and error.

Implementation of the PSO algorithm to solve the models presented in Section 4.2 takes several steps. These are presented in the algorithm overview and in Fig. 3.8. In the next section, the performance of the developed allocation model to integrate SG and IPP into the grid is tested.

Algorithm Overview PSO

- Step 1.** Randomly initialise a population of N_p particles. The particles represent IPP and SG sizes.
 - Step 2.** Evaluate the fitness function (3.39) for each particle.
 - Step 3.** Locate a particle that accompanies the best solution in the neighbourhood.
 - Step 4.** Carry out the steps below until the maximum number of iterations is reached:
 - Step 4a.** For each particle $p = 1, \dots, N_p$: evaluate the fitness function (3.39), and find the best particle position. Next, evaluate the fitness function (3.39), and determine the global best position.
 - Step 4b.** Calculate the velocity of each particle with (3.31) and the corresponding particle position using (3.30).
 - Step 4c.** Terminate the algorithm once the number of iterations, $iter$, equals the preset maximum iteration number.
-

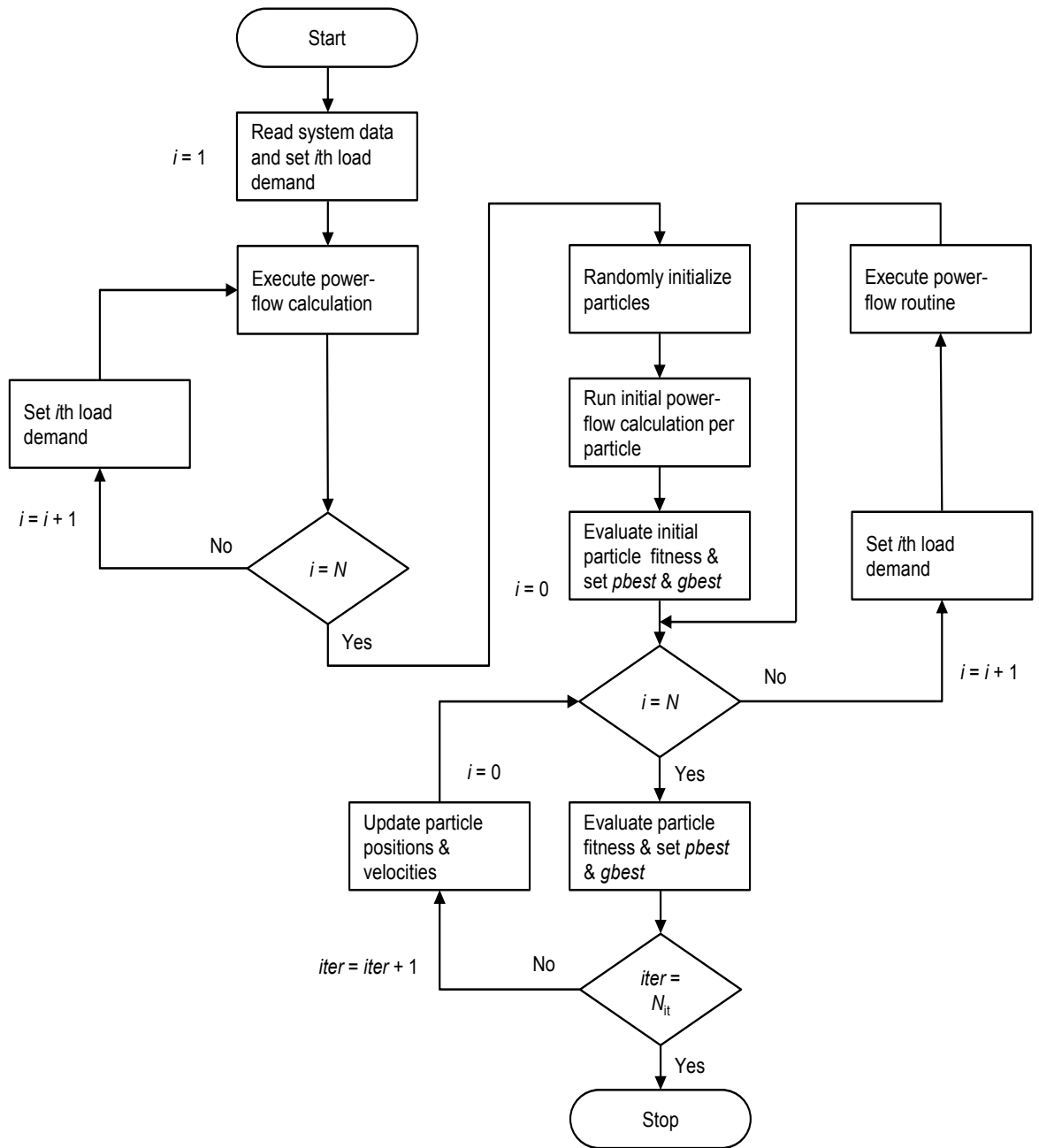


Figure 3.8: Overview of PSO algorithm.

Table 3.6: Input data for the simulations

| | |
|---|-------------|
| Wholesale price of electricity (C^e) | 50 £/MWh |
| Retail price of electricity (C^r) | 55 £/MWh |
| Alternative rate for IPP quota fulfilment (C^b) | 43.3 £/MWh |
| IPP quota (r^o) | 10–35% |
| REC price (C^{rc}) | 42 £/MWh |
| Redistributed payment (C^{rf}) | 5 £/MWh |
| FiT self-generation rate (C^G) | 102.1 £/MWh |
| FiT energy export rate (C^{et}) | 48.51£/MWh |

3.8 Results and Discussion: *Problem 1*

The purpose of this section is to demonstrate the benefits of the proposed model and to ascertain its sensitivity to quota and SG limit variations.

In the proposed SG-IPP allocation model, SG-3 and SG-10 represent the SGs located at bus-3 and bus-10. The same convention is used for IPPs. Table 3.6 contains values of parameters which serve as inputs to the simulations. Again the lower bound for IPP is 5 MW. When an IPP is connected, the cost of RECs is $r^o \times (\text{total energy demand}) \times (C^{rc} - C^{rf})$. To determine the total alternative payment the expression in (3.19) is used. The total cost of the FiT support scheme is calculated as follows: $(\text{total SG energy}) \times C^G + (\text{exported SG energy}) \times C^{et}$.

Two main scenarios are discussed. In the first scenario, quota adjustments are made. The values of r^o are systematically changed from 10% to 35%. SGs are restricted to 100% of local energy demand. In other words, an SG site is not allowed to generate more than it consumes while the IPP quota is adjusted. The SG production limit supply is altered in steps of 10% from 70% to 90% of local demand as the IPP quota is maintained at 25% and 35% in the subsequent scenario. Without any generators in the system, the DISCO earns a profit of £229,186. The solution represents network capacity apportioning preferred by the DISCO mainly because profit is maximised. Network capacity is split between SGs and IPPs at bus-3 and bus-10.

3.8.1 Quota Adjustments

Fig. 3.9 shows the share of each type of generator in the distribution system. The financial implications of the quota adjustments can be seen in Table 3.7. The targets of 10% and 20% correspond to 2.27 MW and 4.55 MW, which are lower than the allowable minimum IPP capacity of 5 MW. However IPPs are connected in any case because SG production levels are limited.

Compared to a distribution system without any SGs and IPPs, the profit is raised by £58,414–£95,084 from £229,186 annually.

The lowest support scheme cost is observed at quotas of 30% and 35%. This is an occurrence that will satisfy both the DISCO and the RA. The DISCO introduces SGs and IPPs, as anticipated by the RA, and minimises expenditure while generating more profit than previously. However, the profit is at its highest when the quota is 25% or lower provided the SG production limit is kept at 100%.

The reason for the lack of IPP capacity at bus-3 can be traced back to the IPP capacity restriction in (3.27). IPPs are only allowed access to the network if they meet the minimum size requirement of 5 MW or higher. Allocating capacity to IPPs at two different locations uses up at least 10 MW of capacity, which leaves an insufficient portion for SGs.

Table 3.7: Quota adjustment results

| SG limit % | Quota % | Profit £ '000 | FiT cost £ '000 | Quota cost £ '000 | Total cost £ '000 |
|---------------|------------|------------------|--------------------|----------------------|----------------------|
| | 10 | 324.27 | 1346.19 | 512.35 | 1858.54 |
| | 20 | 324.27 | 1346.19 | 512.35 | 1858.54 |
| 100% | 25 | 324.27 | 1346.19 | 512.35 | 1858.54 |
| | 30 | 287.76 | 673.10 | 734.96 | 1408.06 |
| | 35 | 287.76 | 673.10 | 734.96 | 1408.06 |

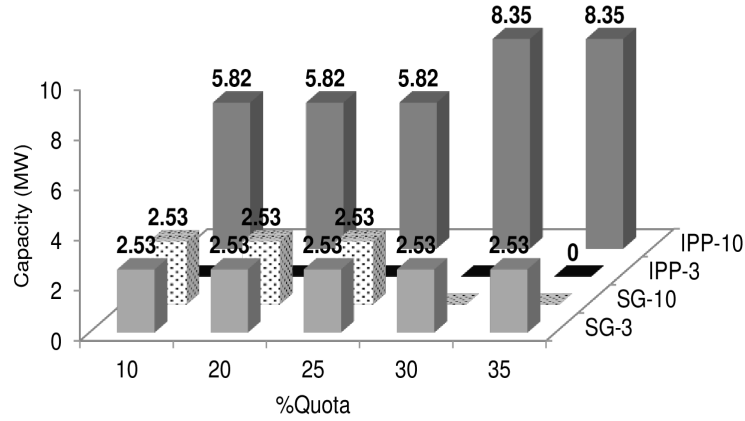


Figure 3.9: Capacity allocation under quota variations.

3.8.2 SG Limit Adjustments

The results of varying the SG production limit are shown in Fig. 3.10. In general, placing stringent limits on SG production is not as profitable for the DISCO as doing the opposite. SGs that produce energy at or below the generation level of 70% are not worth providing network access to compared to increased IPP capacity. The DISCO's profit is purely raised by energy loss reduction. Hence, the most optimal decision is to over-comply with the quota obligation in some situations. The presence of limits also tends to regulate the cost of FiTs. At a quota of 25%, the FiT cost drops from £1.188m to £1.036m when the energy production of SGs is restricted to 90% and 80% respectively (Table 3.8). When the SG production restriction is relaxed, more capacity is allocated to SGs and the DISCO profit increases in return. Unless the production restriction is removed, latent capacity remains in some situations, even if SGs yield more profit for the DISCO than IPPs. This additional capacity is allocated to IPPs since there is no upper cap for the quota mechanism. Again, this results in a high level of compliance when it comes to the quota obligation mechanism.

In some cases it is sufficient to allocate all SG capacity to one bus. As presented in Fig. 3.10, the benefit of one SG location is worth more than two locations, given the

Table 3.8: SG limit adjustment results

| Quota % | SG limit % | Profit £ '000 | FiT cost £ '000 | Quota cost £ '000 | Total cost £ '000 |
|------------|---------------|------------------|--------------------|----------------------|----------------------|
| 25 | 70 | 254.34 | 0.00 | 1028.46 | 1028.46 |
| | 80 | 262.67 | 1036.31 | 561.63 | 1597.93 |
| | 90 | 290.32 | 1188.44 | 536.99 | 1725.43 |
| 35 | 70 | 254.34 | 0.00 | 1028.46 | 1028.46 |
| | 80 | 256.16 | 518.15 | 852.28 | 1370.43 |
| | 90 | 270.32 | 594.22 | 829.65 | 1423.87 |

Table 3.9: Energy exported from SGs as a share of energy consumed locally

| Quota (%) | SG limit (%) | SG-3 (%) | SG-10 (%) |
|-----------|--------------|----------|-----------|
| 25 | 70 | 0 | 0 |
| | 80 | 9.13 | 9.13 |
| | 90 | 14.15 | 14.15 |
| 35 | 70 | 0 | 0 |
| | 80 | 9.13 | 0 |
| | 90 | 14.15 | 0 |

30% and 35% quotas. Unlike the low quota scenarios, the DISCO is better off losing revenue at one bus rather than two. The export portions of energy generated by SGs are presented in Table 3.9. SGs remain an attractive option even with exported energy at just over 9% of local demand.

Implications for Loss Reduction

The solutions are compared in terms of loss reduction with reference to the system without distributed generation. There is a clear distinction between a typical capacity allocation model for generic DGs with loss reduction as the objective, and the model that separates SGs from IPPs and focuses on profit maximisation.

The utilisation of system capacity stands out in the two cases. For minimum losses, total network capacity of 11.68 MW is split almost evenly between bus-3 and bus-

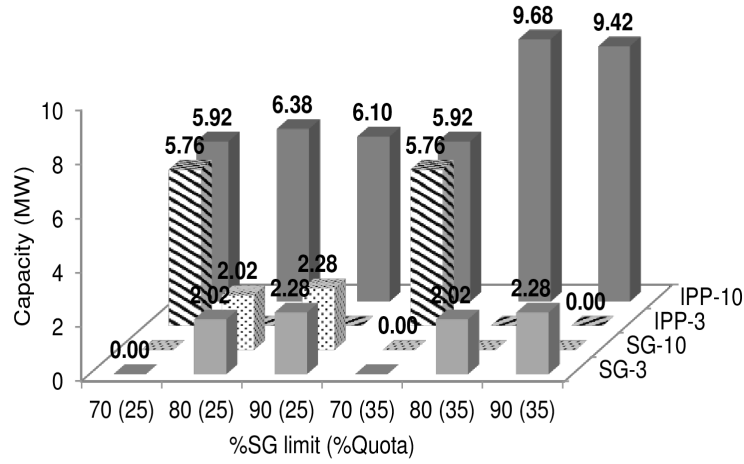


Figure 3.10: Capacity allocation under SG restrictions.

10 when there are no SGs in the system. This occurs at the SG production limit of 70% and below, as illustrated in Fig. 3.11. In contrast, assigning 2.53 MW to SG-3 and SG-4 and 5.82 MW to IPP-10 achieves the highest profit for the DISCO although the resulting total capacity is 10.75 MW. Although significantly lower than the case without distributed generation, losses are not the only determining factor for profit maximisation, hence they are not minimised. Loss reduction for different production allowances ranges from 20.69% to 23.17%.

In terms of constraints, simply allocating all the capacity to SGs causes production level violations, while giving all the capacity to IPPs results in a missed opportunity to increase profit.

3.9 Strict RES Allocation Model: *Problem 2*

In this model the FiT budget constraint is explicitly modelled and can be changed directly whereas the general model only allows indirect FiT budget adjustment through the net production constraint. In fact it is sensitive to the cost of both the FiT and quota obligation schemes. Assuming that as long as the DISCO fulfils but does not exceed the set obligation level, the total cost of purchasing renewable energy certificates

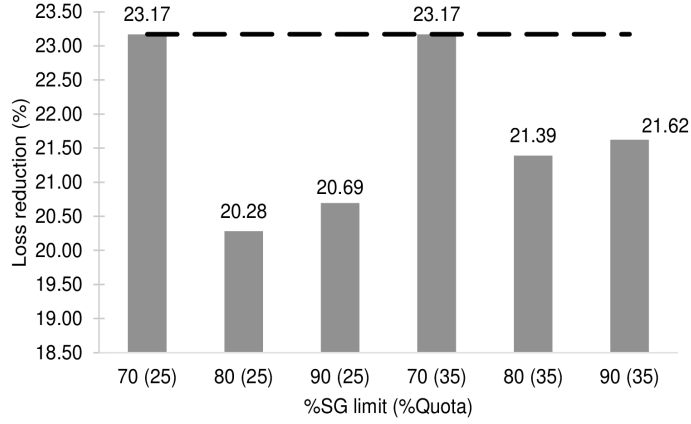


Figure 3.11: Loss reduction performance under SG production variations. Loss reduction (bar). Maximum loss reduction (dash).

(RECs) remains within budget necessary to meet the obligation. An attractive aspect of this model is that it does not impose a hard constraint on the allowed DG capacity. Therefore is easily applies to situations DG brings significant benefit even when the final capacity exceeds the minimum RES requirement.

Problem 2: Strict RES location and capacity allocation

$$\begin{aligned}
 J_Q = & \left(C^b \sum_{t \in T} \left(r^o \sum_{d \in D} P_{L,d}^t - \sum_{i \in I} P_{IPP,i}^t \right) \tau \right) u_c \\
 & + \left(C^{rc} - C^{rf} \right) \sum_{i \in N} \sum_{d \in D} P_{d,i}^{ro} \tau_i u_c + \left(C^{rc} - C^{rf} \right) r^o \sum_{i \in N} \sum_{d \in D} P_{d,i}^l \tau_i (1 - u_c) \quad (3.40)
 \end{aligned}$$

Constraints:

1. Net energy limit:

$$\sum_{t \in T} \sum_{k \in K} P_{SG,k}^t \leq a_L \sum_{t \in T} \sum_{k \in K} P_{SGL,k}^t \quad (3.41)$$

2. SG scheme budget

$$C^G \sum_{t \in T} \sum_{k \in K} P_{SG,k}^t + C^{et} \sum_{t \in T} \sum_{k \in K} P_{k,t}^E (1 - \alpha_{SG,k}^t) (u_{k,t}^e - 1) \leq a_F \quad (3.42)$$

Constraint (3.22) is amended to form (3.41), which allows net energy supply by SGs. The rest of the previously stated constraints, (3.23)–(3.29), remain unchanged. The new constraint (3.42) represents the total payment to SGs i.e. FiT scheme cost. It is comprised of two parts, generation and energy export. Regardless of the split between them, the total cost must be below the specified budget. $C^{\text{rf}} = 0$ if payment redistribution is not supported, which may be the case in some regulatory environments. Again no single DG unit belongs in both SG and IPP classes. Thermal limits are dictated by ratings of lines and transformers. The maximum penetration of distributed generation is limited by the restriction of power flow into the substation. DGs are not allowed to export power to the substation during any interval.

3.10 Results and Discussion: *Problem 2*

3.10.1 Quota Adjustments

A noticeable difference between the strict (*Problem 2*) and general model (*Problem 1*) is that IPP capacity allocation is more in line with the predefined quota when the former is utilised (see Fig. 3.9 and Fig. 3.12). Fig. 3.12 shows capacity distributions under quota variations and SG restrictions. The target of 10% is lower than the minimum allowable IPP capacity. Thus integrating any IPP into the system would result in over-compliance. IPP is still granted minimum capacity, suggesting in this scenario, that over-compliance is more profitable than avoiding the quota penalty. The highest profit is realised when the SG energy is 140% of local energy consumption and quota (as a share of network energy demand) is 0.2 or lower (Table 3.10). However, IPP capacity disappears as a result because the remaining network capacity is less than 5 MW. Unlike the lower obligation levels, the high cost of compliance for quota of 35% secures a 5 MW share of capacity for an IPP.

3.10.2 SG Budget Adjustments

For the same budget, increasing the SG net energy (export) limit causes a shift in SG capacity distribution. The IPP quota is fixed at 25%. Firstly, there can be locational

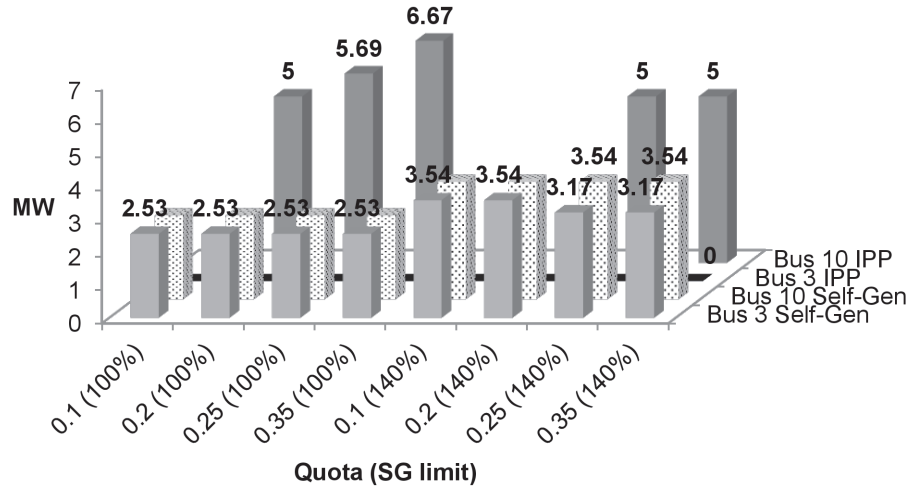


Figure 3.12: Capacity allocation under quota variations and SG restrictions.

Table 3.10: Quota adjustment results

| SG Export % | Quota | Profit £ '000 | FiT cost £ '000 | Quota cost £ '000 | Saving £ '000 |
|-------------|-------|---------------|-----------------|-------------------|---------------|
| 100% | 0.1 | 918.49 | 1346.19 | 234.49 | 0 |
| | 0.2 | 925.86 | 1346.19 | 394.02 | 74.97 |
| | 0.25 | 926.01 | 1346.19 | 500.93 | 85.30 |
| | 0.35 | 925.82 | 1346.19 | 720.73 | 100.01 |
| 140% | 0.1 | 1339.59 | 2014.58 | 234.49 | 0 |
| | 0.2 | 1339.59 | 2014.58 | 468.99 | 0 |
| | 0.25 | 1266.99 | 1892.09 | 511.26 | 74.97 |
| | 0.35 | 1266.08 | 1892.09 | 745.77 | 74.97 |

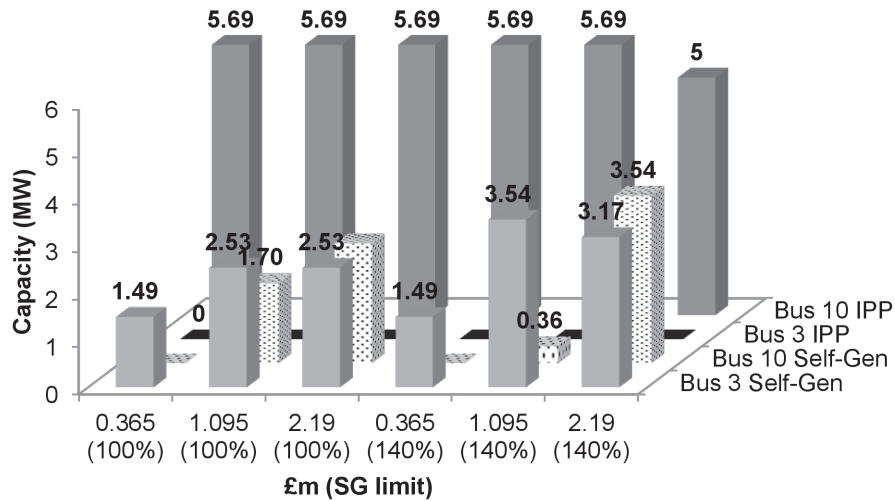


Figure 3.13: Capacity allocation with budget and SG limitations.

capacity displacement; as observed in Fig. 3.13, a budget of 1.095m sees the SG capacity swing from 1.7 MW to 0.36 MW at bus-10 as the net energy limit rises from 100% to 140% of local energy consumption. In both scenarios the full amount is used but a large share of capacity is observed at bus-3 when the export limit is 140%. Secondly, raising the budget to 2.19m again causes capacity displacement. However, this time IPP capacity drops from 5.69 MW to 5 MW. As seen in Table 3.11 only one SG is able to make full use of the allowance in some cases. This means that for the higher SG limit, SG capacity is lower, dropping from 4.23 MW (100% SG limit) to 3.9 MW (140% SG limit). Despite that fact, a higher profit is made in the latter scenario (Table. 3.12). Table 3.12 illustrates the financial impact of the SG limit adjustments. The main observation here is that profit grows with increasing SG export and budget. It is only at a relatively low budget (£365,000) that the profit remains unchanged in both 100% and 140% SG energy scenarios.

Fig. 3.14 illustrates the loss reduction performance. Losses are not as low as in other scenarios for a budget of £0.365m because a smaller amount of network capacity is allocated to both SGs and IPPs. Although SG reaches its full allowance, IPP is limited by disallowed over-compliance.

Capacity limits have a noticeable impact. When SGs make more profit for the

Table 3.11: SG energy production

| Export limit | FiT limit (£ '000) | Bus-3 SG (%) | Bus-10 SG (%) |
|--------------|--------------------|--------------|---------------|
| 100% | 365 | 58.93 | 0 |
| | 1095 | 100 | 67.13 |
| | 2190 | 100 | 100 |
| 140% | 365 | 58.93 | 0 |
| | 1095 | 140 | 14.28 |
| | 2190 | 125.51 | 140 |

Table 3.12: Budget adjustment results for different SG limits

| SG Export % | Budget £ '000 | Profit £ '000 | FiT cost £ '000 | Quota cost £ '000 | Saving £ '000 |
|-------------|---------------|---------------|-----------------|-------------------|---------------|
| 100% | 365 | 410.55 | 364.99 | 500.93 | 85.30 |
| | 1095 | 780.95 | 1095.00 | 500.93 | 85.30 |
| | 2190 | 926.01 | 1346.19 | 500.93 | 85.30 |
| 140% | 365 | 410.55 | 364.99 | 500.93 | 85.30 |
| | 1095 | 836.32 | 1095.04 | 500.93 | 85.30 |
| | 2190 | 1266.99 | 1892.09 | 511.26 | 74.97 |

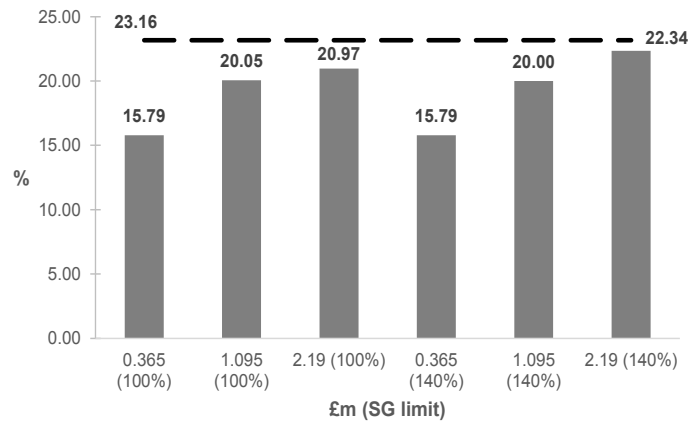


Figure 3.14: Loss reduction performance for SG budget adjustments. Loss reduction (bar). Maximum loss reduction (dash).

DISCO than IPPs, unused capacity may remain in some situations. Since the minimum cap for IPPs is higher than zero, unused capacity that is lower than this cap will be unallocated. This is the capacity that would go to IPPs if the restriction is not instituted. For the DISCO to fill capacity, it would have to sacrifice profit by apportioning less capacity to SGs. Conversely, if IPP supply is favoured and not enough capacity is available, no DG would be connected to the system.

3.11 Summary

The work of this chapter has demonstrated that the power flow and energy arrangements on the edge of the network (i.e., grid and DG supply points) can have a contrasting influence on energy losses and DG size unless curtailment is permitted. DG units are classed as IPP or SG in accordance with industry practice while the requirements of instruments such as quota obligation and FiT schemes provide the policy context.

This chapter further shows that SG and IPP capacity and location can be impacted by the DISCO's desire to maximise profit. These impacts stem from the quota and penalty rate, eroded revenue, export price and net energy allowance. The allocation model, *Problem 1*, favours the uptake of IPP over the quota because SG is not permitted to generate more energy than they consume over the evaluation period. In contrast, *Problem 2* grants SG more network capacity as the net energy limit increases. Additionally, all capacity allocation minimises over-compliance and takes place within budget. The next chapter investigates the incentives available to the DISCO and how they impact the DISCO's decision-making.

Chapter 4

Incentive-Led Allocation of Renewable Independent Power Production and Self-Generation

4.1 Introduction

The preliminary optimisation models described so far ascertain the hosting capacity allocations for RES based on simplifying assumptions. One is guided by OPF and a simple rule for SG and IPP allocation, and the rest investigate a special case of the profit-maximising SG and IPP plan, i.e., the exclusion of SG in quota compliance mechanism, and the assumption of zero export payment and no cost recovery. In other words, their application is limited to a specific incentive permutation. This chapter generalises the formulation of profit maximisation to varying revenue recovery and SG export regulations. It presents a comprehensive optimisation model to determine capacity and location allocations for SG and IPP considering adaptable incentive structures for DISCOs. Numerical analysis is performed on 33-bus and 61-bus test networks, while the results are presented alongside those of an alternative allocation approach.

4.2 SG and IPP Allocation

The work of this chapter presents a model that enables the DISCO to find its most profitable allocation of network capacity to renewable DG. Two classes of generators supported by different policy schemes are studied, in particular IPP and SG. As previously defined, IPP refers to generating plants owned by investors other than the DISCO [25, 26]. SGs are customers who generate energy to be consumed locally first before the surplus is exported to the distribution network.

SG offers some avoidance of the quota obligation because of decreased energy sales. Following the findings of the previous chapter, the capacity illustrations in Fig. 4.1 and Fig. 4.2 are provided to illustrate the process of a simplified capacity allocation example. A single block, marked ‘SG’, represents the amount of SG that would be required to supply all local demand. Two SG blocks along the vertical axis indicate that more energy is generated than is consumed by the SG load. Each column represents a distinct permutation of capacity allocation. Adjacent columns combine to form a grid (called an allocation set). There are three allocation sets. Each allocation set represents the available network capacity that can be filled with different permutations. The first allocation set, noted by one SG block on the left side of Fig. 4.1, shows that a network with a single candidate location accommodates SG alone if the minimum allowed capacity for IPP is higher than its available capacity. As network capacity increases up to the minimum IPP capacity, either SG or IPP can be deployed, but not both. Even higher network capacity offers the possibility to host both or either SG or IPP, as seen with the set on the right side of Fig. 4.1. If SG capacity is bounded by local load, a further possibility arises (Fig. 4.2). A portion of available capacity is allocated, while the rest remains unused when SG reaches a given percentage of local load, 100% in this case (see the set in the middle of Fig. 4.2). The grey blocks are meant to show that no additional SG is allowed due to the local load restriction.

The DISCO owns and operates the distribution system and provides an electricity service to customers. However, the DISCO does not own DG but manages their connection to the system. It must also comply with an externally-set renewable energy mandate. This section describes the DISCO’s financial benefits when evaluating

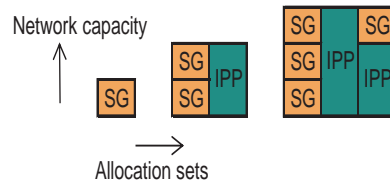


Figure 4.1: Capacity allocation at a single candidate location

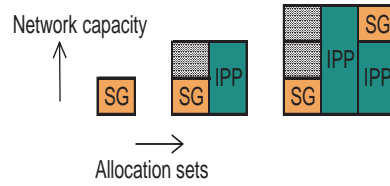


Figure 4.2: Capacity allocation at a single candidate location (restricted SG)

potential IPP and SG connections.

The relevant policy schemes are the quota obligation and feed-in tariff schemes, as described in Section 2.2.2. The quota obligation scheme requires that DISCOs supply a portion of their total load from renewable sources or make an alternative payment to a regulatory body [8]. DISCOs prove compliance by purchasing certificates from IPPs. The alternative payment is usually set higher than the certificate price to encourage renewable energy supply. It represents a penalty if it can not be passed through to ratepayers. SGs are supported by the feed-in tariff incentive scheme. Applicants can be existing consumers who have decided to invest in self-generation. This presents a difficulty for the DISCO as self-generation reduces income from the sale of energy. At the same time exported energy is a potential benefit because it may not come at a cost to the DISCO. In most cases, network capacity is limited by technical constraints that include voltage and thermal limits. The challenge for the DISCO is to allocate the limited network capacity to IPPs and SGs.

The varied incentive impact on profit must be evaluated along with the technical constraints. In short, the DISCO must decide whether to: (1) connect IPPs and purchase renewable energy certificates, (2) simply make alternative payments and connect SGs or (3) select a combination of these options. The solution ensures the DISCO

maintains profitability and fulfils policy scheme requirements at minimum cost.

IPPs and SGs are represented by two different configurations; a sole generator model is adopted for an IPP while an SG is represented by a combined generator and load model. Furthermore, IPPs and SGs impose various distinct constraints on the problem. In fact, there are two additional sets of temporal and binary constraints. One defines the import and export behaviour of SGs and the other reflects the compliance mechanism associated with quota fulfilment.

Another constraint is the capacity restriction for generation under the quota obligation mechanism. Allocation of capacity, in this respect, must take into account the fact that there is a nonzero minimum cap imposed on potential generators. The implication is that discontinuities are added to the capacity constraints.

The optimisation model will be applied to a case study of test distribution networks and analysed numerically. Simulation results will demonstrate the capability of the optimisation model to determine the solution to suit any adjustments in preference for SGs or IPPs. Sensitivity analyses and performance of the model, in terms of energy losses, will also be presented.

4.3 DG Location and Capacity Planning Optimisation Model

This section presents the mathematical details of the optimisation model for SG and IPP location and capacity allocation.

4.3.1 Problem Context

In this problem, a DISCO owns and operates the distribution system and provides an electricity service to all its customers. However, the DISCO does not own candidate DG but manages its connection to the system. This section describes the DISCO's financial benefits when evaluating potential IPP and SG connections, and proposes an optimal planning model to help the DISCO to determine what locations and capacities to promote as owners of IPP and SG seek access to the network. A central authority specifies annually DG eligibility criteria and a quota for renewable energy generation.

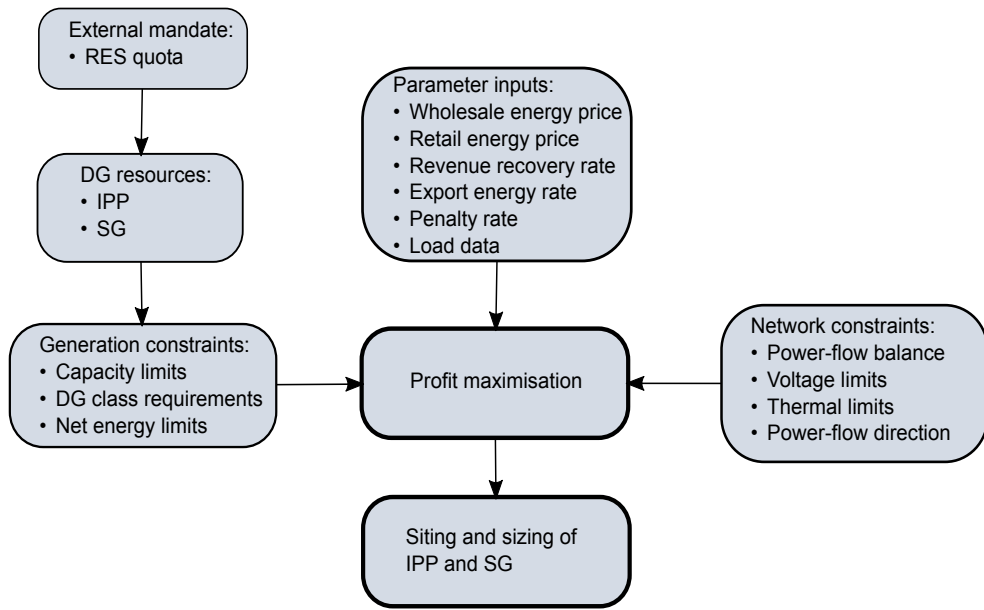


Figure 4.3: Framework used for DG location and capacity planning

The financial benefit of IPP lies in income from energy production, while SG benefits from cost savings due to the reduction of energy consumption and income from energy production. Although the implementation and extent of compensation vary widely and depend on commercial arrangements, the overall structure takes the form of net metering or payments for energy produced and energy exported. In this chapter, the DISCO incurs the cost of surplus energy that is exported to the distribution network [73].

4.3.2 Mathematical Formulation

The framework for the location and capacity planning problem is illustrated in Fig. 4.3. The DISCO receives a mandate to integrate a certain amount of RES from a central authority. It can exercise several options to meet the quota requirement. The options are: accept full financial penalties and not connect renewable DG, combine DG connections and penalty payments, or fill the quota through DG integration. Other inputs consist of price and cost parameters, and representative load and DG resource data. The objective is to maximise profit and in the process, ensure generation and network constraints are satisfied. The outputs of the model are the locations and capacities of

IPP and SG. The next section provides a mathematical formulation of the proposed model.

The objective of the DISCO is to maximise profit, defined in (4.1) as the revenue from the sale of energy minus the cost of energy and quota compliance.

$$\text{maximise } J_P = J_D - J_Q, \quad (4.1)$$

where J_D is the gross profit from the sale of energy and incentives for revenue loss and SG energy export, and J_Q is the penalty payment for renewable energy shortfall. J_D is defined as

$$J_D = \mu_a + \mu_b - \mu_c + \mu_d - \mu_e. \quad (4.2)$$

Without SG, J_D is simply the revenue from energy sales less the cost of wholesale energy ($\mu_a - \mu_c$). Components μ_b , μ_d and μ_e are introduced by the integration of SG with on-site energy use. Fig. 4.4 shows how each one captures the temporal interaction between on-site generation and load. The formulation of the different components is given as follows:

- a) *Energy Retail* (μ_a). This is revenue from selling energy to consumers on the network, expressed as:

$$\mu_a = C^r \sum_{t \in T} \sum_{d \in D} P_{L,d}^t \tau. \quad (4.3)$$

- b) *Revenue Erosion* (μ_b). This term represents reduced revenue due to lower energy consumption at candidate SG locations (Fig. 4.4). The loss of revenue caused by SG is proportional to the local generation level. Of course, when local generation is zero at any SG site, true demand is revealed and the DISCO receives full income as is the case with pure load buses. To obtain μ_b the power difference between local load and generation at SG locations, $P_{k,t}^E$, is recovered using

$$P_{k,t}^E = P_{SGL,k}^t - P_{SG,k}^t. \quad (4.4)$$

To derive retail revenue (4.4) is translated into an energy import or export status,

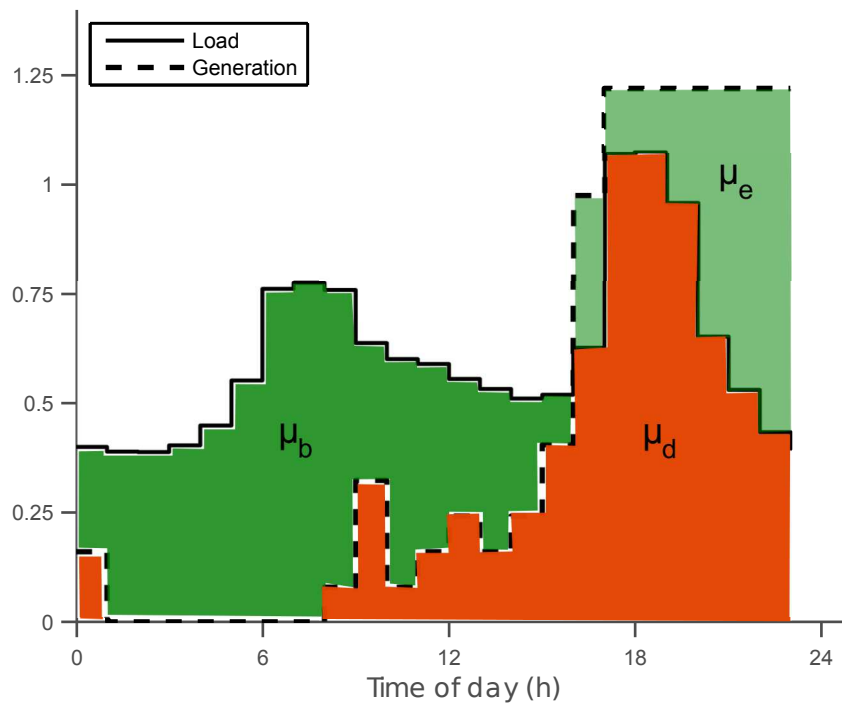


Figure 4.4: Representation of SG impact through regions between load and generation curves

denoted by the notation $u_{k,t}^e$, and expressed by the sign of $P_{k,t}^E$ as follows:

$$u_{k,t}^e := \text{sgn}^+(P_{k,t}^E). \quad (4.5)$$

Using (4.4) and (4.5) μ_b is finally obtained (4.6) as

$$\mu_b = C^r \sum_{t \in T} \sum_{k \in K} P_{k,t}^E \tau u_{k,t}^e. \quad (4.6)$$

- c) *Wholesale Energy Cost* (μ_c). The DISCO purchases energy at the wholesale price, C^e from the substation and IPP to supply all loads not supplied by SG. This term represents the total wholesale energy cost and is given by

$$\mu_c = C^e \sum_{t \in T} (P_s^t + \sum_{i \in I} P_{\text{IPP},i}^t) \tau. \quad (4.7)$$

- d) *Revenue Recovery* (μ_d). This term represents a revenue recovery mechanism, which is the proportion of the total revenue recovered after introducing SG to the system (Fig. 4.4). The costs are recovered from ratepayers or through other means available to the DISCO for dealing with revenue erosion. The expression for revenue recovery is written as:

$$\mu_d = C^{\text{rv}} \sum_{t \in T} \sum_{k \in K} (P_{\text{SG},k}^t u_{k,t}^e + P_{\text{SGL},k}^t (1 - u_{k,t}^e)) \tau. \quad (4.8)$$

- e) *Energy Export Cost* (μ_e). This term is the value the DISCO places on energy exported by SG (Fig. 4.4). The resulting cost represents the DISCO's partial contribution to FiTs and is therefore not recovered from ratepayers.

$$\mu_e = C^{\text{ee}} \sum_{t \in T} \sum_{k \in K} P_{k,t}^E \tau (u_{k,t}^e - 1). \quad (4.9)$$

From (4.9), the unit cost of exported energy can differ from that in (4.7), depending on the value of C^{ee} . For instance, if $C^{\text{ee}} = 0$ a saving in wholesale energy cost is

realised, once the SG capacity rises to levels whereby generation exceeds demand. In contrast, $C^{ee} = C^e$ means that the unit rates of energy from SG, IPP and upstream sources are all identical.

The full mathematical expression for J_D is given as

$$\begin{aligned}
 J_D = & \underbrace{C^r \sum_{t \in T} \sum_{d \in D} P_{L,d}^t \tau}_{\mu_a} + \underbrace{C^r \sum_{t \in T} \sum_{k \in K} P_{k,t}^E \tau u_{k,t}^e}_{\mu_b} - \underbrace{C^e \sum_{t \in T} (P_s^t + \sum_{i \in I} P_{IPP,i}^t) \tau}_{\mu_c} \\
 & + \underbrace{C^{rv} \sum_{t \in T} \sum_{k \in K} (P_{SG,k}^t u_{k,t}^e + P_{SGL,k}^t (1 - u_{k,t}^e)) \tau}_{\mu_d} \\
 & - \underbrace{C^{ee} \sum_{t \in T} \sum_{k \in K} P_{k,t}^E \tau (u_{k,t}^e - 1)}_{\mu_e}. \tag{4.10}
 \end{aligned}$$

In line with the quota obligation, the penalty payment, J_Q , defined in (4.11), is required when the total IPP capacity is lower than the predefined quota, which is given as a percentage of the total energy delivered to consumers.

$$J_Q = \left(C^b \sum_{t \in T} \left(r^o \left(\sum_{d \in D} P_{L,d}^t - \sum_{k \in K} P_{SG,k}^t \right) - \sum_{i \in I} P_{IPP,i}^t \right) \tau \right) u_c, \tag{4.11}$$

where the notation u_c indicates whether or not the DISCO complies with the quota obligation, and is defined by the sign function sgn^+ as:

$$u_c = \text{sgn}^+ \left(\sum_{t \in T} \left(r^o \left(\sum_{d \in D} P_{L,d}^t - \sum_{k \in K} P_{SG,k}^t \right) - \sum_{i \in I} P_{IPP,i}^t \right) \tau \right). \tag{4.12}$$

Of note is the contribution of SG to the quota obligation. SG reduces the quota by decreasing the total energy on which the quota is based.

The objective function ($J_P = J_D - J_Q$) is maximised subject to the following constraints:

- 1) *SG Net Energy Limits.* The total energy produced by SG is expressed in relation to local energy use over the evaluation period, permitting net consumers and net

exporters. Local energy production from SG is, therefore, limited according to the given maximum allowable generation percentage a_L using

$$\sum_{t \in T} \sum_{k \in K} P_{SG,k}^t \leq a_L \sum_{t \in T} \sum_{k \in K} P_{SGL,k}^t. \quad (4.13)$$

- 2) *Power-flow Constraints.* The total power consumption must be equal to the total power supply at each bus, maintaining power-flow balance over the t th interval according to (3.23) for real power and (3.24) for reactive power.
- 3) *Voltage Limits.* The voltage at each bus must be maintained within the appropriate range, defined by (3.25), at all times.
- 4) *Capacity Restrictions.* SG capacity must be in the permitted range, according to (3.26).

The IPP capacity constraint stems from a differentiating rule for SG and IPP. For an IPP connection to be allowed, its capacity must be higher than the upper limit for an SG. Therefore no single DG unit can be categorised as both an SG and an IPP. The requirement is considered by limiting IPP capacity using (3.27), which is interpreted as

$$G_{IPP,i}^{\min} \leq G_{IPP,i} \leq G_{IPP,i}^{\max}, \quad (4.14)$$

for $G_{IPP,i} > 0$. Outside the defined bounds IPP capacity must be set to zero.

- 5) *Thermal Limits.* Thermal loading of lines and transformers must be less than or equal to the levels derived from manufacture ratings and safety regulations. This is given by (3.28).
- 6) *Reverse Power-flow Restriction.* The power flow at the distribution substation must not be negative, meaning the distribution system must not export power upstream. This restriction is enforced using (3.29).

In summary, the location and capacity planning optimisation problem incorporating SG and IPP is formulated by maximising profit, (4.1), subject to constraints (4.13) and

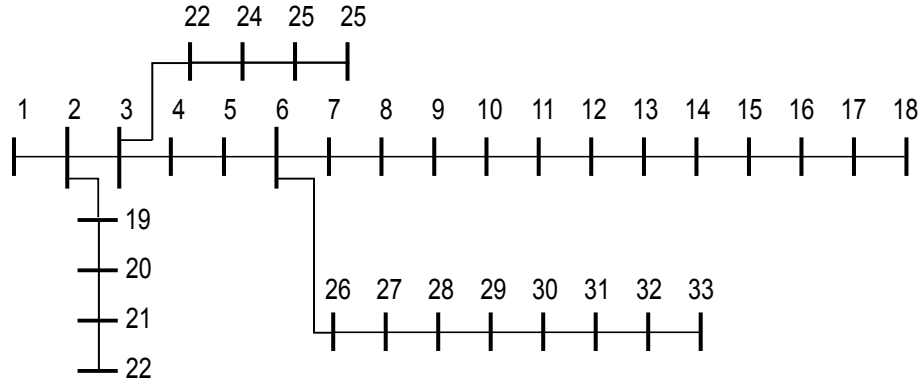


Figure 4.5: The 33-bus distribution system schematic diagram

(3.23)–(3.29). In the next subsections the optimisation model developed here is referred to as the SG and IPP location and capacity optimisation (SILCO) model.

4.3.3 Application to 33-bus and 69-bus systems

The SILCO model is applied to the 33-bus and 69-bus systems shown in Fig. 4.5 and 4.6. Although the model is applicable to any generator classed as SG or IPP, wind energy is the technology selected for all DG in the system for ease of illustration. The associated generation and demand data are provided in Appendix A. Candidate buses for SG and IPP connections on the 33-bus system are 6, 13 and 28. The 69-bus system comprises potential connections at buses 7, 11, 21, 35, 45 and 61. SG-6 and SG-61 represent SG located at bus 6 and bus 61. The same convention is followed for IPP. The voltage variations at each bus of the distribution systems are expected to be within the range $\pm 5\%$. Detailed information on the 33-bus system can be found in [176] and that of the 69-bus system in [177]. The 33-bus system is henceforth identified as Case A and the 69-bus system as Case B. The maximum capacity for a single SG must be lower than 3 MW, which is the minimum value for an IPP. Table 4.1 contains values of parameters which serve as inputs to the base-case simulation. Several other scenarios are created mainly to quantify the performance of the SILCO model in the event of parameter changes.

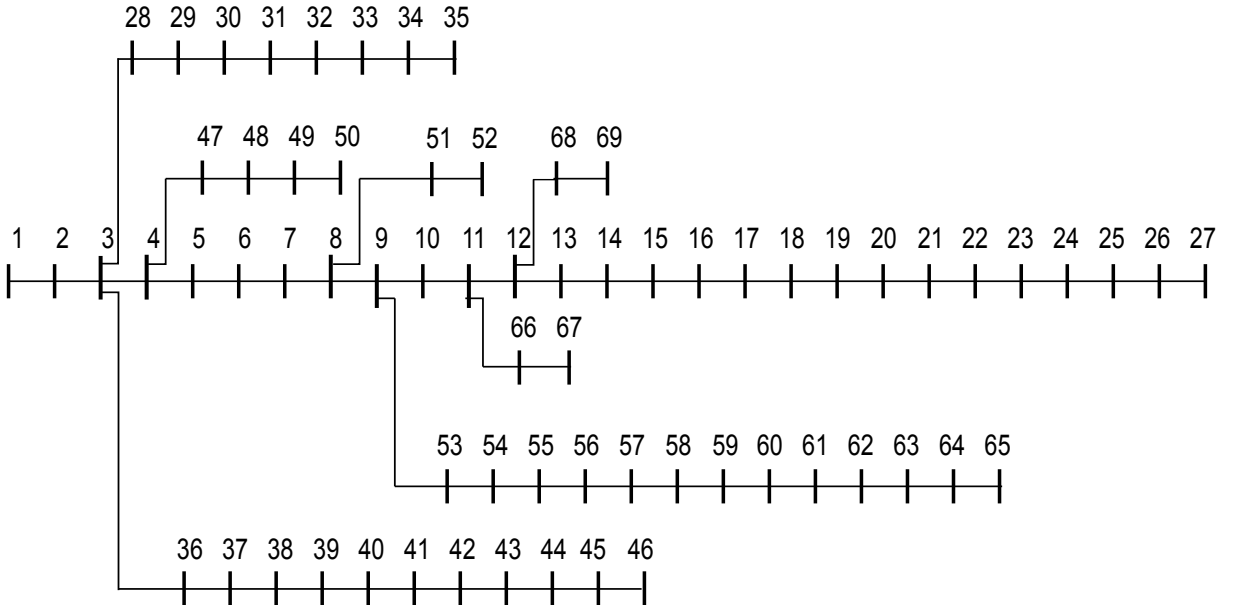


Figure 4.6: The 69-bus distribution system in schematic form

Table 4.1: Parameter values for the base-case simulation

| | |
|---|----------------|
| Wholesale price of electricity (C^e) | 50 £/MWh |
| Retail price of electricity (C^r) | 75 £/MWh |
| Penalty rate for non-compliance (C^b) | 20 £/MWh |
| Revenue recovery rate (C^{rv}) | $0.5C^r$ £/MWh |
| DISCO energy export rate (C^{ee}) | $0.5C^e$ £/MWh |
| SG net energy limit (a_L) | 120% |
| IPP quota (r^o) | 23% |
| Minimum size of IPP (G_i^{\min}) | 3 MW |

4.4 Numerical Results and Discussion

This section demonstrates the benefits of the SILCO model, compares it to other approaches and ascertains its sensitivity to quota, net energy limit, incentives—these are revenue recovery and cost of exported energy—and minimum capacity variations.

4.4.1 Result Comparisons

Here, the base-case simulation results of the SILCO model are benchmarked against those of other methods using parameter data from Table 4.1. The SILCO model is compared with hybrid approaches consisting of a combination of optimisation and rule-based models. For the hybrid approaches, DG location and capacity are determined using a well-established method, which finds the maximum capacity to satisfy voltage and thermal constraints as in [178]. Because the method presents no DG segmentation, SG and IPP capacity shares are consequently apportioned according to predefined rules. For Approach A, DG is not deployed on the network. Approaches B – D correspond to the hybrid approaches composed of the method presented in [178] supplemented with defined rules for DG segmentation. Approach E employs the SILCO model. The description of the approaches considered is given as follows:

Approach A (No DG): System remains free of DG in the presence of quota obligation.

Approach B (IPP only): Find locations that maximise DG capacity. Allocate all of the capacity to IPP.

Approach C (SG only): Find locations that maximise DG capacity. Allocate all of the capacity to SG.

Approach D (Limited SG): Find locations that maximise DG capacity, limit SG integration to 5% of load and allocate the remaining capacity to IPP. This approach reflects current practice in some jurisdictions such as California [179].

Approach E: Apply the SILCO model to determine a combination of SG and IPP at different locations, which maximises profit.

Table 4.2 presents a summary of the results of the various approaches for DG location and capacity planning. Evidently, Approaches B – D produce low profits, constraint violations and inconsistent performance. The main reason for the constraint violations is that only one location yields maximum DG capacity in all these approaches. That is, bus 6 in Case A and bus 61 in Case B. In contrast, the SILCO model (Approach E) maximises profit with respect to all the stated constraints without any violations. In Case A, only Approach A, B and E produce feasible results. Approach C offers the highest profit but the concentration of SG at a single location (bus 6) results in a violation of the limit for SG net energy. It is apparent that Approach E satisfies all constraints and carries increased profit simultaneously. Compared to the system without SG and IPP, the profit is raised by 23.7% to £1.692m. Similar results are found in Case B, where another constraint—the minimum IPP capacity limit—is violated. The reason for the violation is that there is insufficient network capacity (1.221 MW) to satisfy the minimum requirement for IPP capacity (3 MW). Notably, for this case the highest infeasible profit belongs to Approach B. It is thus observed that none of the Approaches B – D is unable to satisfy all constraints and maximise profit in both Case A and B. These results highlight discrepancies that can be expected when there is no inherent representation of SG and IPP within DG planning models. It is apparent that Approach E is the only one that provides feasible profit maximisation.

If the SG net energy and minimum IPP capacity limits are not binding, the results of Approaches B – D will become feasible. Tables 4.3 and 4.4 show the comparison of all the approaches when these constraints are removed. The results also include lack of recovery of lost revenue ($C^{rv} = 0$) following network integration of SG in both the partially and fully constrained scenarios. As expected, Approach E has the highest profit in the partially constrained scenarios for Cases A and B. It is also, yet again, the only feasible approach to provide the highest profits in the fully constrained scenario. Furthermore, it improves the result of Approach C in Case B by 8%. The corresponding profit breakdown of the two approaches is plotted in Fig. 4.7. It can be seen that Approach E suffers less revenue erosion, with lower energy export cost. This is due to the fact that Approach E allocates SG capacity to more locations than

Approach C (Table 4.4).

Table 4.2: Comparison of location and capacity allocation approaches

| | Case A | | Case B | |
|----------|--------------------------|-----------------|--------------------------|-------------------|
| Approach | J_P (£ $\times 10^3$) | Violated const. | J_P (£ $\times 10^3$) | Violated const. |
| A | 1367 | None | 332.05 | None |
| B | 1676.47 | None | 406.92 | min. IPP capacity |
| C | 1839.30 | SG net energy | 350.86 | None |
| D | 1698.83 | SG net energy | 392.53 | min. IPP capacity |
| E | 1692.45 | None | 352.13 | None |

Table 4.3: Comparison of location and capacity allocation approaches ($C^{rv} = 0$)

| Partially constrained (excl. minimum IPP capacity and SG net energy limits) | | | | |
|---|--------------------------|-----------------------|--------------|-----------------|
| | Case A | | | |
| Approach | J_P (£ $\times 10^3$) | SG MW (Bus) | IPP MW (Bus) | |
| A | 1367 | 0 | 0 | |
| B | 1676.47 | 0 | 5.15 (6) | |
| C | 1823.36 | 5.15 (6) | 0 | |
| D | 1685.66 | 0.73 (6) | 4.42 (6) | |
| E | 1823.36 | 5.15 (6) | 0 | |
| Fully constrained | | | | |
| | Case A | | | |
| Approach | J_P (£ $\times 10^3$) | SG MW (Bus) | IPP MW (Bus) | Violated const. |
| A | 1367 | 0 | 0 | None |
| B | 1676.47 | 0 | 5.15 (6) | None |
| C | — | 5.1481 (6) | 0 | SG net energy |
| D | — | 0.7268 (6) | 4.42 (6) | SG net energy |
| E | 1678.05 | 0.091 (13), 0.60 (28) | 4.37 (6) | None |

Table 4.4: Comparison of location and capacity allocation approaches ($C^{rv} = 0$)

| Partially constrained (excl. minimum IPP capacity and SG net energy limits) | | | | |
|---|----------------------------------|---|--------------|-------------------|
| Case B | | | | |
| Approach | J_P ($\text{£} \times 10^3$) | SG MW (Bus) | IPP MW | |
| A | 332.05 | 0 | 0 | |
| B | 406.92 | 0 | 1.22 (61) | |
| C | 316.09 | 1.22 | 0 | |
| D | 382.34 | 0.24 (61) | 0.98 (61) | |
| E | 442.45 | 0.48 (7), 0.74 (45) | 0 | |
| Fully constrained | | | | |
| Case B | | | | |
| Approach | J_P ($\text{£} \times 10^3$) | SG MW (Bus) | IPP MW (Bus) | Violated const. |
| A | 332.05 | 0 | 0 | None |
| B | — | 0 | 1.22 (61) | min. IPP capacity |
| C | 316.09 | 1.22 (61) | 0 | None |
| D | — | 0.24 (61) | 0.98 (61) | min. IPP capacity |
| E | 341.36 | 0.061 (7), 0.22 (11) 0.17 (21) 0.0090 (35) 0.059 (45) | 0 | None |

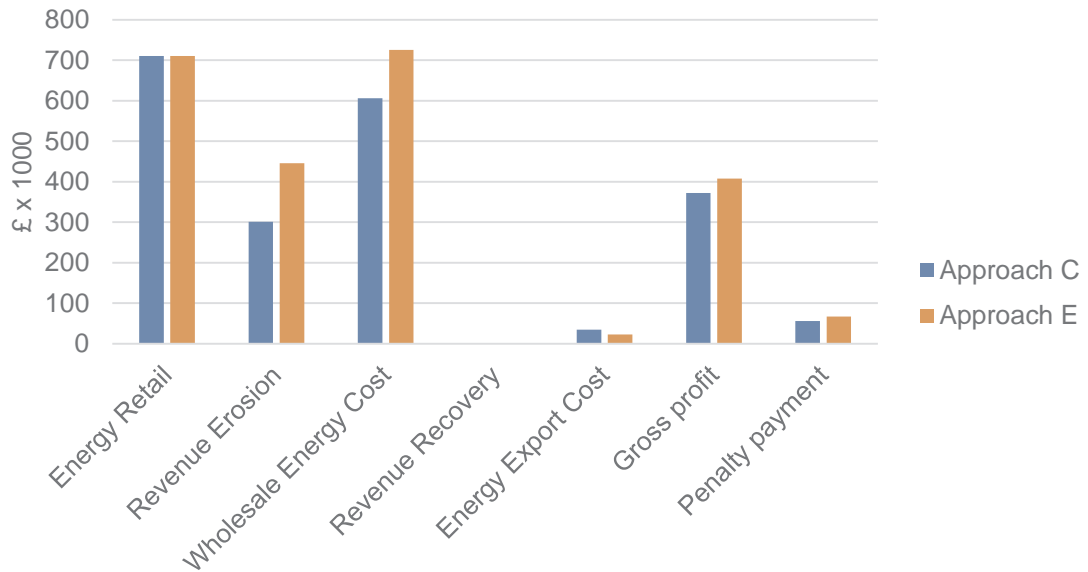


Figure 4.7: Breakdown of DISCO profit

4.4.2 Sensitivity Analyses

In this section, the results of the SILCO model in the presence of parameter changes are analysed.

Quota

The values of r^o are systematically changed from 10% to 35%. All other parameters maintain the values in Table 4.1.

Case A: Fig. 4.8 shows the share of each DG category in Case A. The financial implications of the quota adjustments can be seen in Fig. 4.9. Quotas between 0 and 20% are easily met without filling up network capacity, hence the penetration of SG at all candidate locations is limited by the local net energy limits. Over the same quota range, the profit remains unchanged because the penalty payment for non-compliance is not imposed. It is suggested that the potential loss of revenue due to SG connection coupled with revenue recovery and energy export benefits do not maximise profit at a quota of 25% (4.92 MW). Despite the fact that the maximum network capacity is 5.15 MW, with 0.22 MW (5.15 MW – 4.92 MW) is unused, there is a clear lack of SG (Fig. 4.8). As a result, recovered revenue and cost of exported energy fall to zero.

Eventually, beyond the 25% quota, IPP integration reaches maximum network capacity – 35% quota equals 6.89 MW, which is higher than the maximum available capacity of 5.15 MW. The increasing deficit also increases the penalty payment and therefore reduces profit.

The reason for the lack of IPP capacity at bus 13 and bus 28 can be traced back to the IPP capacity restriction in (4.14). IPP is connected only if it meets the minimum capacity requirement of 3 MW or higher. Allocating capacity to IPP at three different locations uses up at least 9 MW of capacity, which is significantly higher than the maximum network capacity.

Case B: The allocation of network location and capacity using the SILCO model manifests two clear patterns in Case B, which represent repeated allocations as the quota is varied. These patterns are labelled Variation A and B and are shown in Fig. 4.10. Through Variation A the model distributes capacity across multiple buses, and through Variation B, it assigns all network capacity to a single bus. The highest available network capacity is 1.221 MW regardless of parameter changes. Since the minimum capacity limit for IPP is 3 MW, it is again not possible to connect IPP. Therefore, 100% of available capacity is allocated to SG. Variation A is produced for quotas below 30%. Variation B, which provides additional 0.52 MW over variation A, is selected for quota requirements in excess of 30%. Profit from the sale of energy and incentives, J_D , is calculated as £418,861 for Variation A and £406,595 for Variation B. However, Variation B suffers less penalties (J_Q) because of higher capacity. The penalty payment generally increases with rising quota, as seen in Fig. 4.9. It is found that Variation A causes relatively small differences (J_P) between J_D and J_Q at quotas of 25% and below but higher differences for quotas above 25% compared to Variation B. For example, at the quota of 15%, J_P for variation B is £370,243. As seen in Fig. 4.9, J_P for Variation A is clearly higher at £375,340. For a quota of 30%, Variation A produces £331,816 for J_P whereas Variation B yields £333,891, which is the value displayed in Fig. 4.9. This is how the model allocates capacity – by selecting Variation A for quotas below 25%, and Variation B for quotas above 25%.

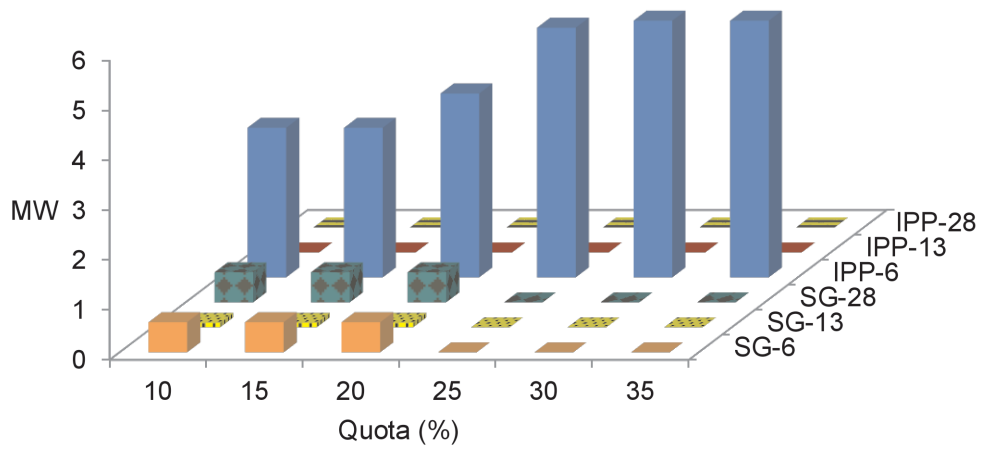


Figure 4.8: DG location and capacity for Case A under quota adjustments

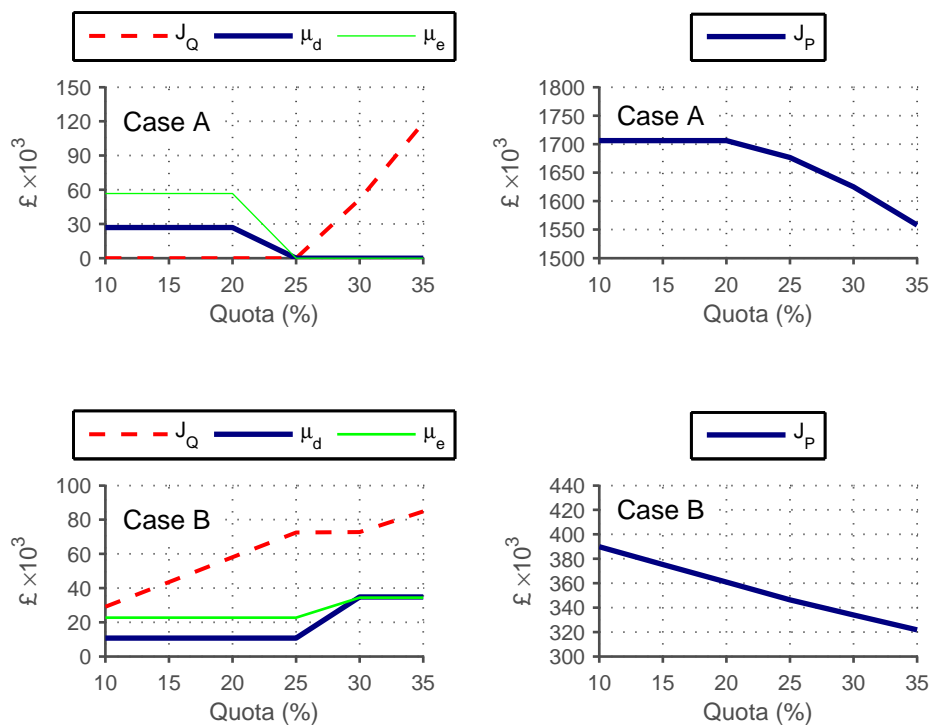


Figure 4.9: Cost and revenue variations due to quota adjustments

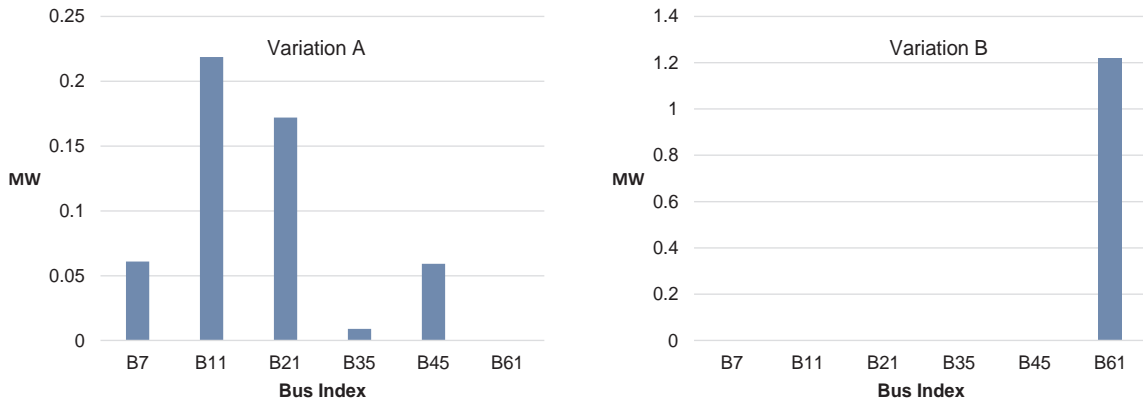


Figure 4.10: SG location and capacity patterns for Case B

Net Energy Limit

The SG net energy limit supply is altered in steps of 20% from 60% to 200% of local demand. Limits below 100% imply that SG units are not allowed to generate more energy than they consume while higher limits permit supply in excess of local consumption.

Case A: The impacts of the SG net energy limit on capacity and financial flows are shown in Fig. 4.11 and Fig. 4.12. In general, restricting SG energy output to levels below local consumption is not as profitable for the DISCO as allowing net energy export, assuming other parameters in Table 4.1 remain unchanged. Net energy limits around 60% and below render SG unprofitable, hence network capacity is solely allocated to IPP (Fig. 4.11). Some capacity remains in these situations because the fixed quota of 23% is less than available network capacity. However, the additional capacity is allocated to IPP since there is no upper cap for the quota mechanism. As a result there is a high level of compliance when it comes to the quota obligation mechanism. When the SG net energy limit is relaxed, more capacity is allocated to SG and the DISCO profit increases in return (Fig. 4.12). However, SG is deployed at bus 6 but displaced at other buses when the limit reaches 140% (Fig. 4.11). The explanation for this change is that SG at one location can export more energy to the network at a cost of $0.5C^e$ without a significant further reduction of revenue from energy sales. Once the net energy limit exceeds 160%, SG begins displacing IPP, causing activation of the penalty charge for quota non-compliance (Fig. 4.11 and 4.12).

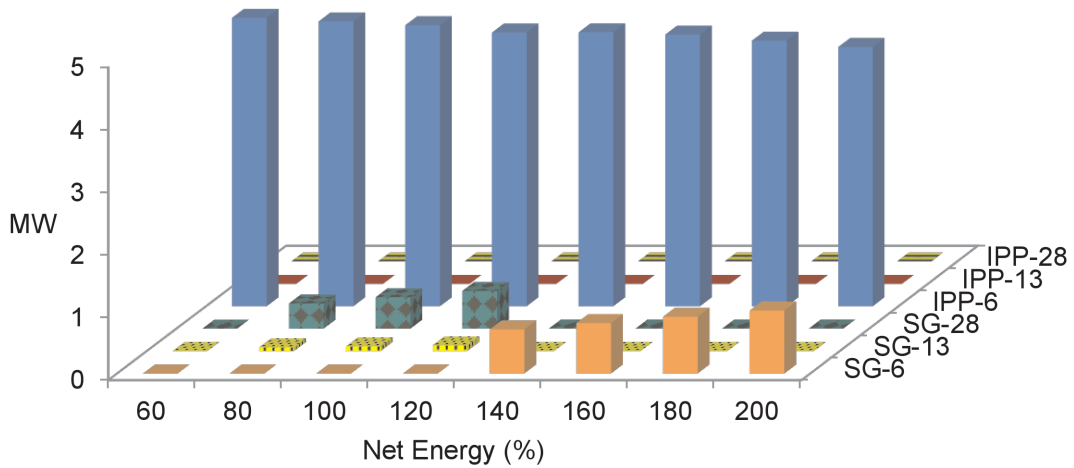


Figure 4.11: Capacity allocation for Case A under net energy restrictions

Case B: Financial results for Case B are shown in Fig. 4.12, with the corresponding capacity details presented in Fig. 4.13. The connection of IPP is ruled out by the minimum limit of 3 MW (Table 4.1), so all network capacity is allocated to SG. Consequently, raising the net energy limit has an immediate effect of decreasing the penalty payment for quota non-compliance (Fig. 4.12). Sharing of capacity between all candidate locations is varied to produce an almost linearly rising profit as the net energy limit is increased.

Revenue Recovery and Energy Export Rate

Fig. 4.14 and 4.15 show variations of financial performance in response to changing recovery and DISCO export rates for Case A and Case B. J_{Q1} , J_{Q2} and J_{Q3} represent penalty payments corresponding to export rates of C^{ee} , $0.5C^{ee}$ and 0, respectively. The same export rates apply for numbered subscripts relating to J_P , μ_d and μ_e .

Case A: Based on Fig. 4.14, the DISCO remains compliant and incurs no financial penalty at the export rates of C^{ee} and $0.5C^{ee}$. When the export rate is 0, the penalty payment increases to £31,251. In general, profit rises proportionally with the revenue recovery rate unless the export rate is equal to the retail price. In this case the profit is constant for all values of C^{rv} from zero up to C^e .

Case B: The DISCO is unable to avoid the penalty payment regardless of revenue

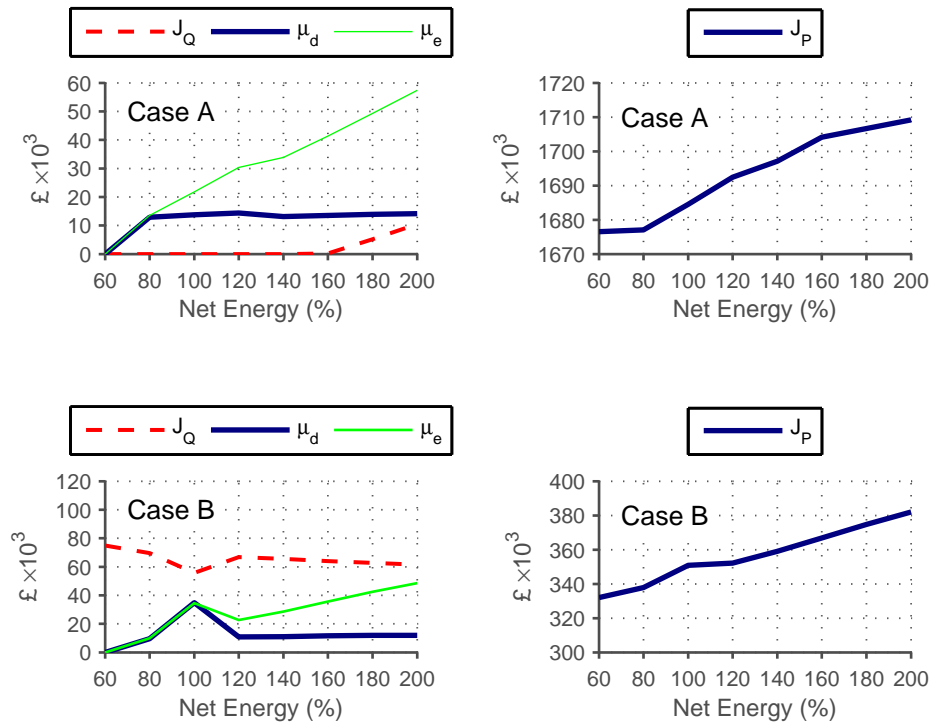


Figure 4.12: Cost and revenue variations due to net energy limit adjustments

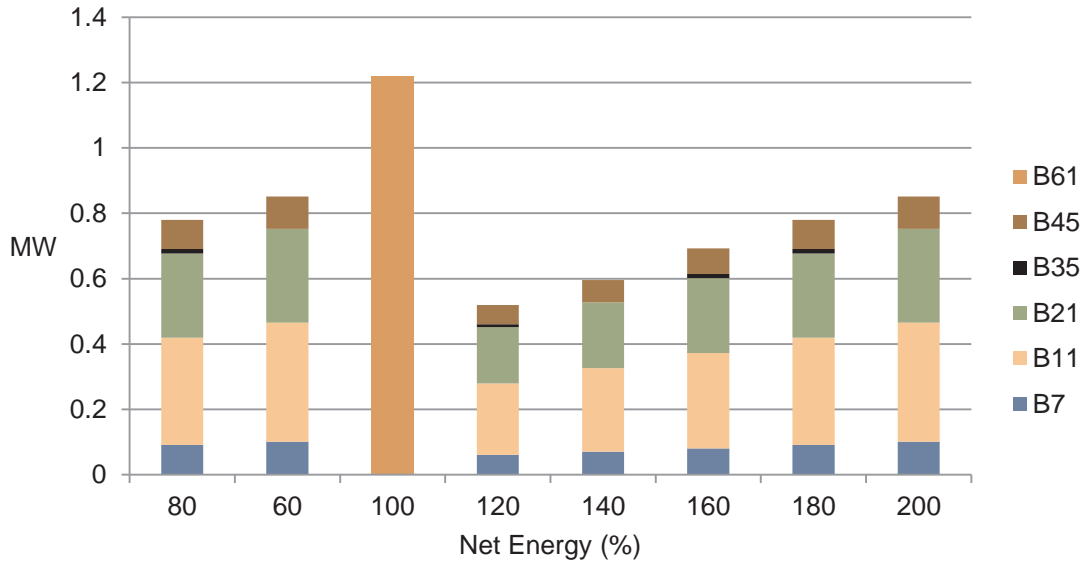


Figure 4.13: Capacity allocation for Case B (69-bus system) under net energy restrictions

recovery and export rates adjustments because the maximum network capacity is less than the prescribed IPP capacity (Fig 4.15). The highest penalty values are observed for the revenue recovery rates below C^e . In contrast, the total revenue recovery and energy export payment increase as the revenue recovery rate rise to $0.5C^e$ and above. As in Case A, the highest profit is encountered when the revenue recovery rate equals the wholesale price and the export rate is zero.

Minimum IPP Capacity Limit

The adjustments of the minimum capacity restriction for IPP are realised by modifying $G_{IPP,i}^{\min}$ in (4.14). This constraint affects how much DG capacity is allocated to IPP and SG, as shown in Table 4.5 for both Cases A and B.

Case A: Any value of $G_{IPP,i}$ that exceeds the quota specification removes the financial penalty for the DISCO as long as system constraints are satisfied. Given the network constraints (3.25), (3.28) and (3.29), raising the lower limit to 6 MW leaves out IPP connections. This is because the maximum DG capacity on the network is 5.15 MW. At all candidate locations, maximum SG capacity is reached, amounting to a total of 1.3 MW (Table 4.5). In other words, the binding constraint for SG is the net

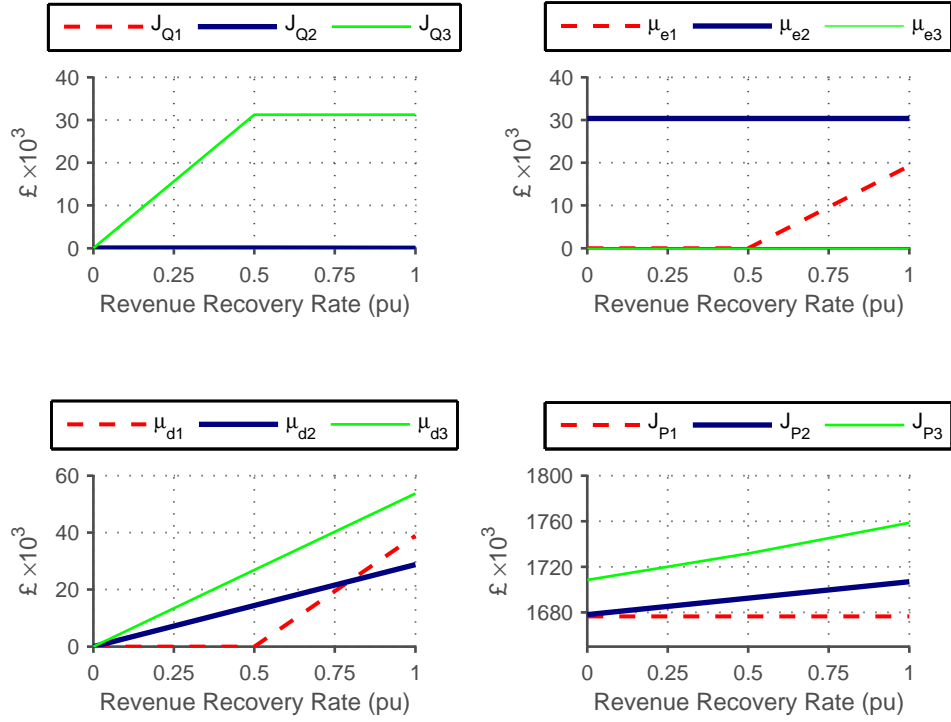


Figure 4.14: Cost and revenue variations under revenue recovery and energy export rate adjustments for Case A

Table 4.5: Impact of restricting IPP capacity

| Case A | | | |
|----------------|----------------------------------|---------|----------|
| IPP limit (MW) | J_P ($\text{£} \times 10^3$) | SG (MW) | IPP (MW) |
| ≥ 4 | 1692.45 | 0.69 | 4.37 |
| ≥ 5 | 1676.47 | 0 | 5 |
| ≥ 6 | 1418.1 | 1.3 | 0 |
| Case B | | | |
| IPP limit (MW) | J_P ($\text{£} \times 10^3$) | SG (MW) | IPP (MW) |
| ≥ 1 | 408.63 | 0.22 | 1 |
| ≥ 1.22 | 406.92 | 0 | 1.22 |
| ≥ 2 | 352.13 | 1.068 | 0 |

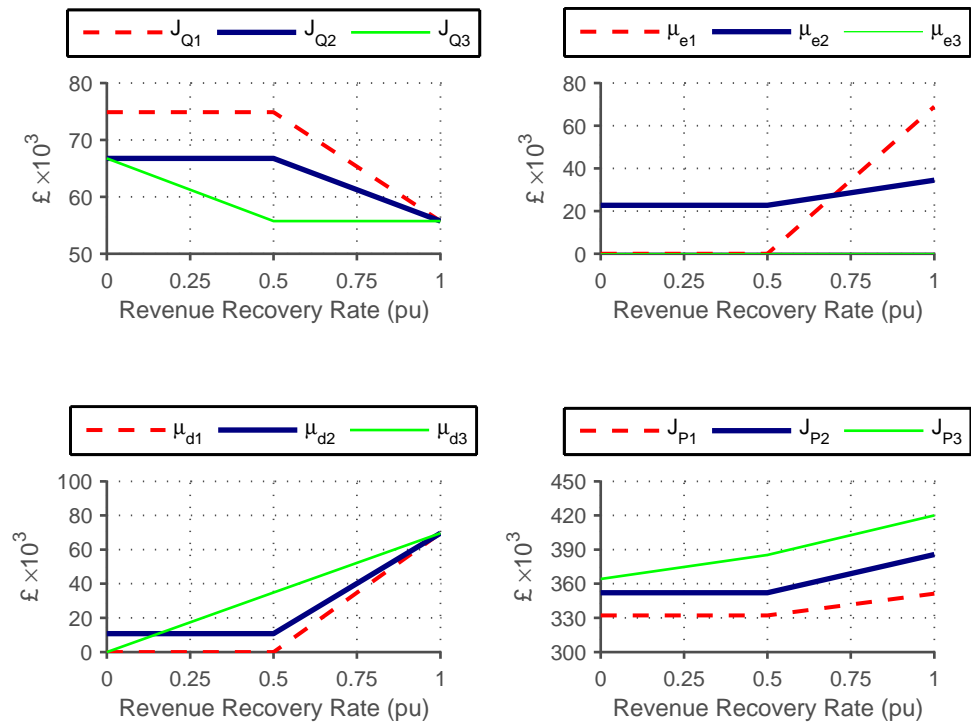


Figure 4.15: Cost and revenue variations under revenue recovery and energy export rate adjustments for Case B

energy limit. As a result, it is observed that raising the net energy limit will result in more use of network capacity by SG in the absence of IPP.

Case B: As seen in Table 4.5, IPP connection is only made possible by much lower capacity restrictions. An apparent issue in the preceding analyses is that, Case B has insufficient capacity for IPP at 3 MW and above. However, it does open up to IPP at limits of 1 MW and below. In fact, the observation is that, to ensure that capacity is allocated to both IPP and SG in the two cases, the minimum limit must be set at 1.22 MW or lower. Therefore, relaxation of the minimum capacity cap encourages better diffusion of network capacity.

4.4.3 Application to Renewable Energy Programmes

The utility of the SILCO model can be viewed from the perspectives of the DISCO and the RA. For the DISCO, the model provides the capability to guide decisions for investors by releasing information and incentives for connection opportunities that increase or preserve profits. As discussed, the DISCO can maximise profit given varying regulatory conditions. However, revenue recovery and discounted export cost will lead to increased prices for ratepayers. Therefore, the results of the model must also carry relevance for regulation. Consequently, the profit of the DISCO must not be too low to discourage DG integration, nor be excessively high, which can lead to a substantial increase in profits at the ratepayers' expense.

There are other ways in which the model can be used in this context. During the design of renewable energy programmes, the model can assist in deciding the limits for minimum IPP capacity and SG net energy. The minimum limit for IPP can have the effect of displacing either IPP or SG. If the limit is too high, IPP investors will be subjected to high costs of connection and delays due to the requirements for network reinforcement or access higher voltage levels. A high net energy limit can lead to concentration of SG at a few locations. This means that only a few DISCO customers will be able to obtain network access, further undermining the roll-out of RESs.

Because there are many subtle differences between market environments worldwide, the model is intended to exploit similarities (e.g., the presence of SG and IPP) without

being overly focused on the particularities a single region. In specific cases, such as the California market, net metering would replace FiT. In this case the model can be easily modified because it would not be necessary to determine financial flows of exported energy in every time step, but at the end of the accounting period using accumulated energy. In the UK, the energy retail price would be replaced by connection and use-of-system charges considering the role of a DNO.

4.5 Summary

In this chapter, an optimal DG location and capacity planning model is developed in which DG is separated into IPP and SG in accordance with the requirements of practical policy schemes such as quota obligation and FiT. The unique capability of the proposed optimisation model is that the DISCO will be able to determine how much capacity to allocate to IPP and SG and where to locate it without relying on predefined rules. In particular, it is shown that the DISCO will be able to integrate location and capacity evaluations for SG and IPP to maximise profit. The obligation to meet renewable energy quota and the import-export impact of SG are embedded within the model. This ensures the most favourable financial position for the DISCO, considering the trade-off between penalty payments and RES connection. Furthermore, financial aspects specific to SG connection—revenue recovery and energy export payment—are considered to complete the objective function. Unlike hybrid models with predefined rules for IPP and SG deployment, the model presented here is able to satisfy constraints unique to each DG class while maximising profit. Notably, the hybrid models violate the SG net energy and IPP size limits because the import and export capability of SG and the lower bound of IPP capacity are not taken into account. In contrast, the proposed model enables facilitation of IPP and SG connections while raising profits by up to 23.7% without violating any constraints. It is also demonstrated with the obtained model that changes in renewable energy quota, net energy limit and other parameters cause variations in location and the distribution of capacity between IPP and SG as profit is maximised.

Chapter 5

Targeted RES Integration through Optimised Network Incentives

5.1 Introduction

The previous chapter presented the perspective of the DISCO exposed to RES obligations and their effective incentives. The main observations are that maximising the DISCO's profit changes SG and IPP capacities and locations depending on cross-subsidies from network users. This chapter considers the RA's role, which is to set achievable RES targets and ensure that the costs incurred by users are not excessive. The RA must thus determine RES targets, and incentives that best align with the capacity of the host network. The developed models are derived from the idea that profits can be decoupled from the retail aspects of the DISCO's business. To satisfy the financial requirements of the DISCO and its customers the models optimally adjust the quota penalty as well as the revenue recovery and energy export incentives. Key to these adjustments is the ability to adapt to network constraints.

5.2 Penalty Technique for Quota Commitment

RES quota or target setting has characteristics similar to reward/penalty schemes found in service quality regulation, energy loss incentive and energy efficiency programmes [38–41]; the main features shared in common being, a performance requirement, and the imposition of a penalty when the requirement is not met. The penalty mechanism is founded on the principle that the penalty payment can be avoided if the DISCO can comply with the quota obligation. Whenever the DISCO is in compliance, increasing the penalty price will have no bearing on the profit. Conversely, if the DISCO is unable to meet the obligation, it will absorb (internalise) the penalty and lower its profit in the process. An obvious factor in this inability is lack of additional network capacity. In fact, under the current regulatory framework in California, for instance, the penalty can be waived if the DISCO demonstrates that there is insufficient on its system [180].

Obviously the regulating authority (RA) does not know beforehand with absolute certainty the actual maximum capacity for RES in a given network. But it can come up with reasonable estimates through the proposed optimisation model by predefining tentatively the approximate network capacity (ANC). The ANC is based on the notion that the RA can enforce a minimum RES capacity requirement as a precondition to the relaxed compliance requirements. As a start, the ANC can be chosen arbitrarily and then tuned based on the results of the optimisation model. The upper bound for ANC is the maximum RES capacity considering technical constraints only, without SG/IPP classification.

On this basis, a mathematical model to optimise the sharing of capacity between SGs and IPPs is developed in the following section.

5.3 Full Mathematical Formulation

This section presents the mathematical formulation of the RA or central planning authority's perspective. The objective of interest is the minimum deviation of the

DISCO's profit from the baseline profit, expressed as

$$\text{minimise } J_P = ((J_D - J_Q) - J_C)^2, \quad (5.1)$$

because $J_D - J_Q > J_C$, the function J_P is monotonic and can be simplified to

$$\text{minimise } J_P = (J_D - J_Q) - J_C. \quad (5.2)$$

The baseline profit is assigned J_C and is the amount that maintains DISCO profit based on the required (allowed) revenue. It must take into account the needs of both the DISCO and its customers. J_Q is the penalty payment for renewable energy shortfall. J_D is the profit from the sale of energy and incentives for revenue loss and SG energy export. The penalty payment applies when the total IPP capacity is lower than the pre-specified quota. Note that integration of SG reduces the absolute quota by decreasing the amount of energy required by consumers. This benefit is highlighted in [169]. The expression for calculating the associated penalty payment is

$$J_Q = \left(C^b \sum_{t \in T} \left(r^o \left(\sum_{d \in D} P_{L,d}^t - \sum_{k \in K} P_{SG,k}^t \right) - \sum_{i \in I} P_{IPP,i}^t \right) \tau \right) u_c. \quad (5.3)$$

Note that in the function (5.3) the penalty rate C^b is a variable. As defined in (4.12), the variable u_c indicates whether or not the DISCO complies with the quota obligation. When the DISCO complies with this obligation for IPP integration, it only incurs the electricity costs represented by J_D . If the DISCO fails to fill the IPP quota the total cost becomes the sum of alternative payments and the wholesale cost. The retail part of the objective function, J_D , is defined as

$$J_D = \mu_a + \mu_b - \mu_c + \mu_d - \mu_e, \quad (5.4)$$

where the different components are outlined below.

- a) μ_a : This is income from selling energy to the network's consumers.
- b) μ_b : This term represents revenue loss due to reduced energy consumption at can-

didate SG locations. The loss of revenue caused by SG is proportional to the local generation level. Of course, when local generation is zero at any SG site true demand is revealed and the DISCO receives full income as is the case with pure load buses.

- c) μ_c : The DISCO purchases energy at the wholesale price, C^e from the substation and IPP to supply all loads not supplied by SG. This term represents the total wholesale energy cost.
- d) μ_d : This term represents a revenue recovery mechanism, which is the proportion of the total revenue lost by introducing SG to the system. In this formulation the recovery rate C^{rv} is an incentive variable.
- e) μ_e : This term is the value that the DISCO places on energy exported by SG. It contains the incentive variable C^{ee} , which is the energy export rate. The value of μ_e is the DISCO's partial contribution to FiTs and is thus not recovered from ratepayers. Naturally, the DISCO's incentives and penalty cost savings amount to zero if the DISCO does not allocate any capacity to RES.

The full mathematical expression for J_D is given by

$$\begin{aligned}
 J_D = & \underbrace{C^r \sum_{t \in T} \sum_{d \in D} P_{L,d}^t \tau}_{\mu_a} + \underbrace{C^r \sum_{t \in T} \sum_{k \in K} P_{k,t}^E \tau u_{k,t}^e}_{\mu_b} - \underbrace{C^e \sum_{t \in T} \left(P_s^t + \sum_{i \in I} P_{IPP,i}^t \right) \tau}_{\mu_c} \\
 & + \underbrace{C^{rv} \sum_{t \in T} \sum_{k \in K} \left(P_{SG,k}^t u_{k,t}^e + P_{SGL,k}^t (1 - u_{k,t}^e) \right) \tau}_{\mu_d} \\
 & - \underbrace{C^{ee} \sum_{t \in T} \sum_{k \in K} P_{k,t}^E \tau (1 - u_{k,t}^e)}_{\mu_e}. \tag{5.5}
 \end{aligned}$$

Based on the above formulation, it is possible to integrate the variation of retail revenue and costs before and after the connection of RES. This enables a more direct approach to incorporate the impact of RES and maintain profit decoupling. A well-known decoupling mechanism is one which preserves specific revenue baselines determined in the rate case [18]. This mechanism is illustrated in Fig. 5.1. The approach proposed here

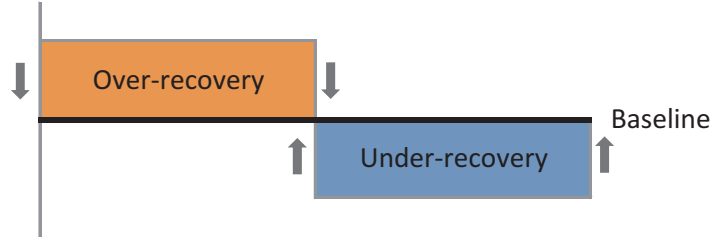


Figure 5.1: Revenue restoration via decoupling. This mechanism removes fluctuations (over-recovery and under-recovery) in revenue over time.

can be deemed performance-based decoupling, as it preserves specific revenue and cost margins, sets performance incentives and limits performance-related costs. It particularly focuses on the costs of RES support and energy retail. The above formulation can be viewed through the lens of revenue regulation, typically formulated according to (5.6) [122, 181]. In revenue regulation, the required revenue R_T in period T is given by

$$R_T = (R_{T-1} + \gamma \Delta N_c)(1 + \kappa - X) \pm Z. \quad (5.6)$$

where γ is the customer growth adjustment factor, ΔN_c is the change in the number of customers, κ is the consumer or retail price index, X is the efficiency factor, and Z is the adjustment factor for events that can not be controlled by the company. Once an RES programme is established, the revenue in period T can be calculated as

$$R_T^{RES} = (R_{T-1}^{RES} + \gamma \Delta N_c)(1 + \kappa - X) \pm Z. \quad (5.7)$$

The revenue is adjusted to include the impact of RES according to:

$$R_{T-1}^{RES} = \mu_a + \mu_b + \mu_d. \quad (5.8)$$

Suppose customer growth factor, efficiency factor (for other initiatives besides DG integration) and uncontrollable events are not dependent on RES penetration, and remain constant. The retail function can then be expressed as $J_D = R_{T-1}^{RES} - \mu_c - \mu_e$.

J_P is minimised subject to constraints, which are described as follows:

- 1) *Quota and FiT scheme budget.* The purpose of this constraint is to quantify and limit the costs of RECs and FiTs. The FiT structure allows for a generation rate and an export rate. This is expressed formally as:

$$C^G \sum_{t \in T} \sum_{k \in K} P_{SG,k}^t + C^{et} \sum_{t \in T} \sum_{k \in K} P_{k,t}^E (u_{k,t}^e - 1) + C^{rc} \sum_{t \in T} \sum_{i \in I} P_{IPP,i}^t + \mu_d - \mu_e \leq a_F. \quad (5.9)$$

- 2) *Target for self-generation:*

$$\sum_{t \in T} \sum_{k \in K} P_{SG,k}^t \geq r^S \quad (5.10)$$

- 3) *Minimum profit requirement:*

$$J_Q + J_D \geq J_C \quad (5.11)$$

- 4) *Net energy limits:* The local energy production limit is enforced by the constraint (4.13).

- 5) *Power-flow constraints:* The power-flow balance at the t -th interval follows (3.23) for real power and (3.24) for reactive power.

- 6) *Voltage and thermal limits:* The voltage constraint (3.25) at each bus and thermal loading limits (3.28) for branch elements remain unchanged.

- 7) *Capacity restrictions:* SG and IPP capacity must be in the permitted range. The limits are defined separately in (3.26) and (3.27).

- 8) *Reverse power-flow restriction:* The power flow at the distribution substation must not be negative, meaning the distribution system must not export power upstream. This constraint (3.29) allows internal bidirectional power flow only between branches operating at the same voltage level.

This optimisation model provides the capability to determine incentives, quota penalty along with targeted SG and IPP capacity allocations so that revenue and quota compliance costs maintain the DISCO's baseline profit. In the next sections the optimisation model is referred to as the regulated SG and IPP location and capacity optimisation

(RSILCO) model. The DISCO revenue recovery rate (C^{rc}), energy export rate (C^{ee}) and quota penalty (C^b) are now variables in addition to those that were established in Chapter 4—the SG and IPP capacity and power-flow variables. The optimisation model utilises the predefined ANC to ensure that the quota penalty is only adapted once network capacity is filled. If the ANC is unknown the optimisation model can be extended to ensure that available capacity is exploited with every stated quota. This extension is described in the next section.

5.4 Optimised Profit Deviation and Capacity Determination

Energy cost is given by the product of power, time and price. In the above formulation the power and price (incentive rate) are variables. One therefore contends with the following key issue: how to differentiate between values of power and price which collectively produce equivalent costs of energy.

The DISCO may have the desire to maximise capacity for any specified incentive. In this sense, an additional objective may be necessary. The outcome can be achieved by replacing the original objective with a weighted sum of two objectives – profit deviation and capacity maximisation. The weight, w_p defines the trade-off between the deviation and capacity. The extended objective function is solved with respect to the original constraints through

$$\text{minimise } J_P = w_p(J_Q + J_D - J_C) - (1 - w_p)\left(\sum_{k \in K} G_{SG,k} + \sum_{i \in I} G_{IPP,i}\right), \quad (5.12)$$

where $w_p \leq 0$. A single value of the weight, w_p , is selected. However, it is possible to find the pareto set, also known as non-dominated set, by varying the value of w_p .

5.5 Numerical Results and Discussion

Two features of regulation are considered: financial incentives, and performance assessment. To gain an understanding of achieved performance improvements, the RSILCO

model is benchmarked against decoupling. Firstly, an evaluation of decoupling is given—decoupling symmetrically restores the revenue in line with a historical test year; revenue growth or the influences of declining sales are damped alike (Fig. 5.1). Secondly, its results are compared to those of the regulation optimisation model, which can be viewed as performance-based (conditional) decoupling. It aims to restore the allowed profit provided specific performance objectives, such as predefined RES quota, are met. This mechanism captures changing overall revenue as well as the energy and network cost impact of DG connections. The DISCO is compensated in proportion with declining energy consumption and rising energy export. The two models are compared, bearing in mind that the standard decoupling mechanism does not have the capacity to incorporate RES policy instruments.

To further the understanding of the regulation optimisation model an empirical analysis is presented, focusing on the 69-bus distribution system first described in Section 4.3.3. The DISCO’s minimum required profit for the network is £391,000. The amount is taken as the baseline for analysis of actual profits considering incentives and quota compliance costs. The studies that follow demonstrate the role of the RA in determining the appropriate incentives to maintain the profit baseline using the optimisation model, (5.1)-(5.12).

5.5.1 Optimal Base Case

By restricting deviation from the baseline, the DISCO will release excess DG-related benefits or claim their associated costs in order to restore the base profit. Hence the profit remains steady as the quota increases. At this point it is useful to be reminded of the varied profits observed in Section 4.4. Namely, administratively set incentives lead to wide-ranging results as the DISCO pursues maximum profits. Here, the incentives are calculated based on the given budget and available network capacity. Because of its low capacity, the 69-bus network can not accommodate IPP. Thus compliance is achieved mainly by means of incentives and penalty relaxation.

In response to the rising quota obligation, the share of RES generally increases (Table 5.1). But once the ANC of 21% is reached, penalty reduction becomes an

Table 5.1: Network capacity, DISCO incentives and RES costs: *min* profit deviation

| | 10% | 20% | 30% | 40% | 50% | 50% |
|---------------------|-----------|-----------|-----------|------------|-----------|-----------|
| Bus-7 (MW) | 0 | 0 | 0.015 | 0.11 | 0.11 | 0.037 |
| Bus-11 (MW) | 0 | 0.38 | 0.40 | 0.40 | 0.40 | 0 |
| Bus-21 (MW) | 0 | 0.072 | 0 | 0 | 0 | 0.094 |
| SG Bus-35 (MW) | 0 | 0 | 0 | 0 | 0 | 0.012 |
| Bus-45 (MW) | 0.014 | 0 | 0 | 0 | 0 | 0 |
| Bus-61 (MW) | 0 | 0 | 0.56 | 0.74 | 0.74 | 1 |
| Total SG (MW) | 0.014 | 0.45 | 0.98 | 1.25 | 1.25 | 1.14 |
| Recovery Rate | 0.048 | 0 | 0 | 1 | 1 | 0.777 |
| Export rate (pu) | 0.727 | 1 | 0.643 | 1 | 1 | 0 |
| Penalty Rate (pu) | 20 | 20 | 4 | 20 | 16 | 4 |
| Budget (£) | 1,726,058 | 2,026,854 | 2,327,649 | 2,628,445 | 2,929,240 | 2,929,240 |
| Actual Cost (£) | 5,045 | 200,417 | 413,308 | 668,439 | 668,430 | 603,150 |
| Penalty Cost (£) | 36,489 | 66,865 | 17,783 | 111,894 | 111,895 | 29,087 |
| Quota Cost (£) | 0 | 0 | 0 | 0 | 0 | 0 |
| SG cost (gen., £) | 4,978 | 157,618 | 382,842 | 533,534.41 | 533,527 | 544,068 |
| SG cost (export, £) | 11.70 | 42,799 | 48,221 | 64,377 | 64,378 | 24,103 |
| SG cost (total, £) | 4,989 | 200,417 | 431,063 | 597,911 | 597,904 | 568,171 |

option, as the 30%-quota scenario shows. However, the reduced penalty does not imply lack of additional capacity because higher quotas still produce a higher share of RES. What the relaxed penalty does, in this case, is add another viable option to meeting the quota obligation. A better sign of exhausted capacity lies in the quotas of 40 and 50%. The two scenarios have equal capacities and create the highest RES shares. For both scenarios, the recovery and export rates are at their upper limits. The difference is that the 50% scenario requires the penalty rate to be reduced in order to reach the base profit. One way to ensure minimum deviation from the base point is to lower the penalty further. This is demonstrated by alternative set of capacity allocations for the 50% quota requirement (last column of Table 5.1). It maintains nearly the same profit residual (actual profit minus baseline/base profit). This is done with slightly less RES capacity (1.14 MW) and with reduced penalty, recovery and export rates. As a result, the option is less costly. The total annual incentive cost is £603,150 whereas the higher capacity of 1.25 MW costs £668,430 in incentives. In addition, the network capacity is distributed to more locations. Another useful comparison can be made in terms of energy loss. The annual energy loss for the 1.14 MW option is 216.11 MWh. It is a figure that is 14.45 MWh lower than the 230.56 MWh produced by the 1.25 MW capacity option. Furthermore, it is below the energy losses obtained for all lower quota allocations.

Upon inspection, it observed that the ANC allows numerous capacities that can, at times, be below the desired amount of RES. If the RA prefers a stricter allowance, the ANC can be raised. This action will only permit relaxation of the penalty for capacities near the upper bound for the network. However, raising the ANC too high will not reduce the penalty even when full network capacity is reached. Therefore, the incentives (recovery and export rates) reach their upper limits, after which the lack of alternatives will lead to profits that are lower than the baseline or historical year values.

5.5.2 Adapting to Changing Energy Consumption

DISCOs are exposed to uncertainties in the load their networks serve. Customer demand drives sales volumes over time. The ability of the optimisation model to mitigate these changes is assessed by uniformly modifying the total load in the 69-bus network. The load is decreased or increased by 3% before running the simulations in quota steps from 10% to 50%. A consistent occurrence through the energy consumption scenarios is that for rising quota, allocated network capacity and incentives tend to increase whereas the penalty declines. Indeed, the network capacity approaches the network limit, same for the incentives and penalty.

Load decrease or increase cases cause a reduction or increase of energy sales. Since the quota requirement is expressed as a percentage of energy consumption, it will also rise or decline in the same manner. As a result, there will be a deficit or surplus in profit over the baseline. The impact is discernible in regards to the cost of DISCO incentives.

The different costs of incentivising the DISCO as the load varies are given in Table 5.2. A complete representation of these costs comprises both the incentives and savings in penalty payments. The total (deemed) costs do allow for a fair comparison in all arising scenarios, for instance, lower incentives and penalty versus high incentives and penalty. The increased load scenario projects the lowest costs attributed to the DISCO relative to the base load, whereas the reduced load scenario exhibits higher costs. These costs are necessitated by the need to reinstate the profit baseline. Even more so because the IPP capacity is lacking in the 69-bus system.

5.5.3 Maximising Capacity Under Binding Support Scheme Costs

The impact of further restrictions to the planning model is assessed. The model must not only minimise the profit deviation but also maximise capacity considering a more limited budget. It can be seen (Table 5.3-5.5) that the capacity grows with the quota input and costs are generally lower than the single objective cases in Sections 5.5.1 and 5.5.2. Although the model maximises capacity for every quota, the smaller available budget prevents very high capacity from being connected under low quota. Hence, there

Table 5.2: DISCO retail support and penalty costs (LD: load decrease, BC: base case, LI: load increase)

| | | 10% | 20% | 30% | 40% | 50% |
|----|---------------------|--------|--------|---------|---------|---------|
| LD | DISCO Incentive (£) | 17,002 | 49,766 | 75,981 | 114,748 | 91,471 |
| | Savings (£) | 0 | 0 | 50,154 | 0 | 86,487 |
| | Equivalent Cost (£) | 17,002 | 49,766 | 126,135 | 114,748 | 177,958 |
| BC | DISCO Incentive (£) | 67.43 | 44,114 | 31,947 | 136,882 | 136,881 |
| | Penalty Saving (£) | 0 | 0 | 71,131 | 0 | 27,974 |
| | Equivalent Cost (£) | 67.43 | 44,114 | 103,078 | 136,882 | 164,855 |
| LI | DISCO Incentive (£) | 42,733 | 59,982 | 69,023 | 134,362 | 129,648 |
| | Penalty Saving (£) | 6,060 | 12,436 | 0 | 0 | 0 |
| | Equivalent Cost (£) | 48,793 | 72,418 | 69,023 | 134,362 | 129,648 |

are no costly RES allocations for low quotas unlike the more permitting budgets seen in the previous section. Furthermore, the penalty is only relaxed at higher quotas.

The penalty saving, μ^{ps} , is calculated as follows:

$$\mu^{\text{ps}} = \left((C^{\text{b}} - C_{\text{act}}^{\text{b}}) \sum_{t \in T} (r^{\text{o}} \sum_{d \in D} P_{L,d}^t - \sum_{i \in A} P_{\text{IPP},i}^t) \right) u_{\text{c}}. \quad (5.13)$$

The total DISCO incentive (μ^{inc}) for SG connection is the sum of the revenue recovery and export saving,

$$\mu^{\text{inc}} = \mu_d + (C^{\text{e}} - C^{\text{ee}}) \sum_{t \in T} \sum_{k \in K} P_{k,t}^{\text{E}} (1 - u_{k,t}^{\text{e}}). \quad (5.14)$$

The overall or equivalent DISCO incentive is the sum of (5.13) and (5.14). The overall incentive excludes the retail surplus caused by changing load. The surplus is discussed in subsection 5.5.4.

Table 5.6 and Fig. 5.2 show the equivalent incentive and its breakdown under varying quota obligation. The DISCO incentive costs are consistently lower than those characterised by higher budget and no explicit capacity maximisation. Although the budget constraint does not guarantee the lowest costs, by remaining below the budgeted amount, these results do show its consistent effectiveness. From Fig. 5.2 it is apparent

Table 5.3: Generation capacity and financial impact (LD: load decrease): *min* profit deviation and *max* generation capacity

| | 10% | 20% | 30% | 40% | 50% |
|----------------------------|---------|---------|---------|---------|-----------|
| Bus-7 (MW) | 0.00 | 0.10 | 0.10 | 0.10 | 0.03 |
| Bus-11 (MW) | 0.38 | 0.38 | 0.38 | 0.16 | 0.20 |
| Bus-21 (MW) | 0.00 | 0.00 | 0.30 | 0.00 | 0.00 |
| Bus-35 (MW) | 0.00 | 0.01 | 0.02 | 0.00 | 0.00 |
| Bus-45 (MW) | 0.00 | 0.10 | 0.10 | 0.00 | 0.00 |
| Bus-61 (MW) | 0.00 | 0.00 | 0.00 | 1.00 | 0.82 |
| Total SG (MW) | 0.38 | 0.60 | 0.90 | 1.27 | 1.05 |
| Recovery rate (pu) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Export rate (pu) | 0.40 | 0.67 | 0.35 | 0.00 | 0.24 |
| 6% LD Penalty rate (£/MWh) | 20.00 | 20.00 | 12.00 | 4.00 | 4.00 |
| Budget (£) | 226,232 | 452,464 | 678,697 | 904,945 | 1,131,172 |
| Actual cost (£) | 157,764 | 270,492 | 368,944 | 692,551 | 567,283 |
| Penalty cost (£) | 31,728 | 60,367 | 50,676 | 20,958 | 27,290 |
| Quota cost (£) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| SG cost (gen., £) | 131,059 | 209,467 | 311,487 | 615,974 | 491,473 |
| SG cost (export, £) | 41,722 | 66,062 | 99,160 | 39,053 | 28,907 |
| SG cost (total, £) | 172,782 | 275,529 | 410,648 | 655,029 | 520,381 |
| Actual profit | 390,550 | 390,550 | 390,550 | 390,550 | 390,550 |
| Bus-7 (MW) | 0.09 | 0.05 | 0.00 | 0.10 | 0.11 |
| Bus-11 (MW) | 0.00 | 0.00 | 0.25 | 0.32 | 0.00 |
| Bus-21 (MW) | 0.00 | 0.31 | 0.31 | 0.31 | 0.00 |
| Bus-35 (MW) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bus-45 (MW) | 0.00 | 0.00 | 0.10 | 0.11 | 0.00 |
| Bus-61 (MW) | 0.00 | 0.00 | 0.00 | 0.00 | 0.81 |
| Total SG (MW) | 0.09 | 0.36 | 0.65 | 0.83 | 0.92 |
| Recovery rate (pu) | 0.89 | 1.00 | 0.84 | 1.00 | 1.00 |
| Export rate (pu) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 3% LD Penalty rate (£/MWh) | 20.00 | 20.00 | 20.00 | 20.00 | 8.00 |
| Budget (£) | 226,232 | 452,454 | 678,697 | 904,929 | 1,131,161 |
| Actual cost (£) | 43,416 | 174,748 | 312,551 | 403,022 | 514,480 |
| Penalty cost (£) | 34,837 | 65,893 | 92,773 | 118,830 | 58,355 |
| Quota cost (£) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| SG cost (gen., £) | 31,536 | 125,618 | 227,805 | 289,306 | 427,295 |
| SG cost (export, £) | 9,254 | 37,907 | 66,800 | 88,472 | 25,077 |
| SG cost (total, £) | 40,790 | 163,525 | 294,605 | 377,778 | 452,372 |
| Actual profit (£) | 390,550 | 390,550 | 390,550 | 390,550 | 390,550 |

Table 5.4: Generation capacity and financial impact (BC: base case): *min* profit deviation and *max* generation capacity

| | 10% | 20% | 30% | 40% | 50% |
|-------------------------|---------|---------|---------|---------|-----------|
| Bus-7 (MW) | 0.02 | 0.00 | 0.00 | 0.00 | 0.08 |
| Bus-11 (MW) | 0.00 | 0.00 | 0.24 | 0.40 | 0.40 |
| Bus-21 (MW) | 0.00 | 0.31 | 0.32 | 0.26 | 0.00 |
| Bus-35 (MW) | 0.00 | 0.00 | 0.02 | 0.00 | 0.01 |
| Bus-45 (MW) | 0.00 | 0.00 | 0.01 | 0.11 | 0.00 |
| Bus-61 (MW) | 0.04 | 0.00 | 0.00 | 0.00 | 0.59 |
| Total SG (MW) | 0.06 | 0.32 | 0.57 | 0.77 | 1.07 |
| Recovery rate (pu) | 0.59 | 1.00 | 1.00 | 1.00 | 0.75 |
| Export rate (pu) | 0.00 | 0.83 | 1.00 | 1.00 | 1.00 |
| BC Penalty rate (£/MWh) | 20.00 | 20.00 | 20.00 | 20.00 | 12.00 |
| Budget (£) | 226,232 | 452,464 | 678,697 | 904,945 | 1,131,161 |
| Actual cost (£) | 23,574 | 148,422 | 275,477 | 372,738 | 540,143 |
| Penalty cost (£) | 36,158 | 68,731 | 97,803 | 125,041 | 87,078 |
| Quota cost (£) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| SG cost (gen., £) | 20,620 | 110,509 | 199,327 | 267,271 | 437,319 |
| SG cost(export, £) | 45.22 | 34,511 | 56,421 | 82,608 | 55,944 |
| SG cost (total, £) | 20,665 | 145,020 | 255,747 | 349,879 | 493,263 |
| Actual profit (£) | 390,550 | 390,550 | 390,550 | 390,550 | 390,551 |

Table 5.5: Generation capacity and financial impact (LI: load increase): *min* profit deviation and *max* generation capacity

| | 10% | 20% | 30% | 40% | 50% |
|----------------------------|---------|---------|---------|---------|-----------|
| Bus-7 (MW) | 0.00 | 0.00 | 0.00 | 0.00 | 0.12 |
| Bus-11 (MW) | 0.00 | 0.25 | 0.41 | 0.41 | 0.00 |
| Bus-21 (MW) | 0.00 | 0.00 | 0.00 | 0.32 | 0.00 |
| Bus-35 (MW) | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 |
| Bus-45 (MW) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bus-61 (MW) | 0.19 | 0.00 | 0.18 | 0.23 | 1.00 |
| Total SG (MW) | 0.19 | 0.25 | 0.59 | 0.98 | 1.12 |
| Recovery rate (pu) | 0.02 | 1.00 | 1.00 | 0.00 | 1.00 |
| Export rate (pu) | 0.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 3% LI Penalty rate (£/MWh) | 20.00 | 20.00 | 20.00 | 16.00 | 12.00 |
| Budget (£) | 226,232 | 452,454 | 678,681 | 904,929 | 1,131,172 |
| Actual cost (£) | 67,253 | 116,193 | 278,844 | 423,456 | 643,714 |
| Penalty cost (£) | 36,303 | 72,001 | 278,844 | 98,629 | 90,854 |
| Quota cost (£) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| SG cost (gen., £) | 66,847 | 85,350 | 206,198 | 341,172 | 540,091 |
| SG cost(export, £) | 0.00 | 20,678 | 45,717 | 82,283 | 31,332 |
| SG cost (total, £) | 66,847 | 106,028 | 251,915 | 423,456 | 571,408 |
| Actual profit (£) | 390,550 | 390,550 | 390,550 | 390,550 | 390,550 |
| Bus-7 (MW) | 0.09 | 0.05 | 0.00 | 0.10 | 0.11 |
| Bus-7 (MW) | 0.00 | 0.00 | 0.00 | 0.10 | 0.00 |
| Bus-11 (MW) | 0.00 | 0.00 | 0.42 | 0.42 | 0.00 |
| Bus-21 (MW) | 0.00 | 0.27 | 0.33 | 0.33 | 0.33 |
| Bus-35 (MW) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bus-45 (MW) | 0.00 | 0.00 | 0.11 | 0.00 | 0.00 |
| Bus-61 (MW) | 0.35 | 0.00 | 0.00 | 0.23 | 0.88 |
| Total SG (MW) | 0.35 | 0.27 | 0.86 | 1.09 | 1.21 |
| Recovery rate (pu) | 0.00 | 1.00 | 1.00 | 0.11 | 1.00 |
| 6% LI Export rate (pu) | 0.00 | 0.39 | 0.35 | 1.00 | 1.00 |
| Penalty rate (£/MWh) | 20.00 | 20.00 | 20.00 | 20.00 | 16.00 |
| Budget (£) | 226,232 | 452,464 | 678,681 | 904,945 | 1,131,161 |
| Actual cost (£) | 122,711 | 110,974 | 356,192 | 476,581 | 657,695 |
| Penalty cost (£) | 0.00 | 73,950 | 98,516 | 124,857 | 122,170 |
| Quota cost (£) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| SG cost (gen., £) | 122,711 | 92,180 | 300,710 | 377,885 | 0.00 |
| SG cost(export, £) | 0.00 | 26,348 | 95,298 | 93,837 | 49,197 |
| SG cost (total, £) | 36,258 | 118,528 | 396,025 | 471,726 | 584,131 |
| Actual profit (£) | 390,550 | 390,553 | 390,550 | 390,550 | 390,550 |

Table 5.6: Breakdown of DISCO support costs (LD: load decrease, BC: base case, LI: load increase): *min* profit deviation and *max* generation capacity

| | | 10% | 20% | 30% | 40% | 50% |
|-------|---------------------|--------|--------|--------|---------|---------|
| 6% LD | DISCO Incentive (£) | 27,986 | 63,054 | 60,503 | 77,778 | 76,719 |
| | Penalty Saving (£) | 0 | 0 | 33,784 | 83,834 | 109,161 |
| 3% LD | DISCO Incentive (£) | 12,165 | 50,294 | 86,798 | 116,433 | 87,955 |
| | Penalty Saving (£) | 0 | 0 | 0 | 0 | 87,532 |
| BC | DISCO Incentive (£) | 2,955 | 38,973 | 77,884 | 108,016 | 104,542 |
| | Penalty Saving (£) | 0 | 0 | 0 | 0 | 58,052 |
| 3% LI | DISCO Incentive (£) | 406.16 | 31,479 | 74,050 | 84,811 | 104,593 |
| | Penalty Saving (£) | 0 | 0 | 0 | 24,657 | 60,570 |
| 6% LI | DISCO Incentive (£) | 0 | 19,603 | 58,409 | 101,581 | 124,272 |
| | Penalty Saving (£) | 0 | 0 | 0 | 0 | 30,542 |

that the DISCO support costs generally increase with growing quota and load. This means that the support costs depend on the rate at which the policy-makers aim to reach the RES goal, i.e., the cost of getting from 10% versus that of reaching 30% from 10%. Despite these changing factors, the optimisation model ensures profit remains unaffected.

5.5.4 Comparison of Regulation Models

Under a standard decoupling mechanism, the revenue must be kept constant regardless of changes in energy sales. Furthermore, the mechanism does not account for costs or savings of RES integration. The basic decoupling mechanism studied here maintains the margin between energy sales and wholesale energy costs, which can, therefore, account for volumetric energy discrepancies. It is assumed that with decoupling, there is no explicit objective except that RES allocation costs must be within the allocated budget. Therefore, the same RES capacities and locations determined by the optimisation model are used for the standard decoupling model. Furthermore, decoupling by itself does not make an explicit provision for the DISCO's contribution to the SG export payment. The DISCO thus contributes the wholesale rate under standard decoupling. The quota

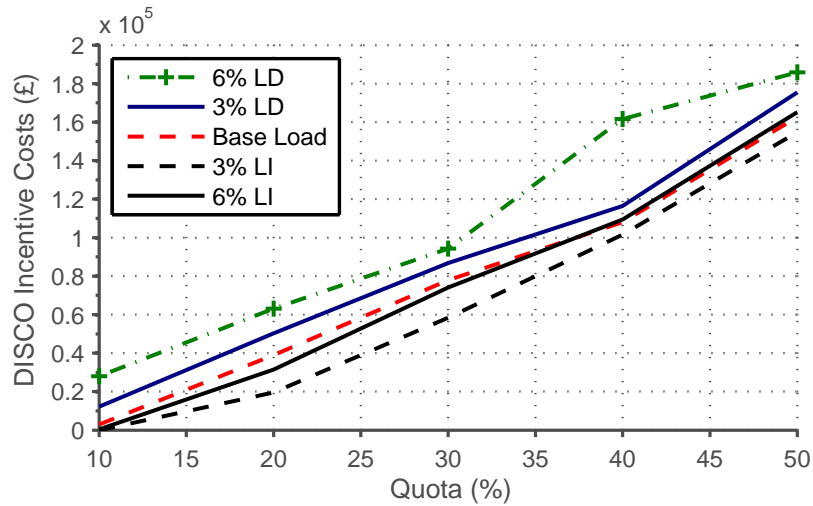


Figure 5.2: DISCO incentive (support) costs as network load varies. LD: load decrease, LI: load increase.

compliance is imposed because without it the DISCO remains agnostic to any level of network access for RES.

For the same amount of generation capacity and locations as the optimised model, standard decoupling maintains revenue but fails to maintain profit. The focus on revenue only excludes the penalty payments, which constitute the cost of non-compliance and are instead factored to the cost and profit calculation. Without decoupling and quota consideration, the profit starts off higher than the baseline but then declines because of the increasing share of SG. See Fig. 5.3. The deviation in profit considering decoupling and quota penalty is more pronounced, decreasing linearly with the quota. Decoupling with no RES policy coordination also has an impact on RES programme support costs. Suppose that the DISCO connects an arbitrary amount of RES for a given quota, say 10%. If RES at this quota is 0.92 MW, corresponding support costs would be £1,320. Customers would subsequently suffer price increases that are disproportionate to the required RES quota. On the other hand the RSILCO model restores profit in line with the available network capacity. Unlike decoupling, the optimisation model is capable of linking retail and RES policy aspects. Fig. 5.4 illustrates how the penalty rate adapts with an increasing RES quota. It useful to point out that the network capacity is not necessarily equal to the specified quota. That is why the penalty

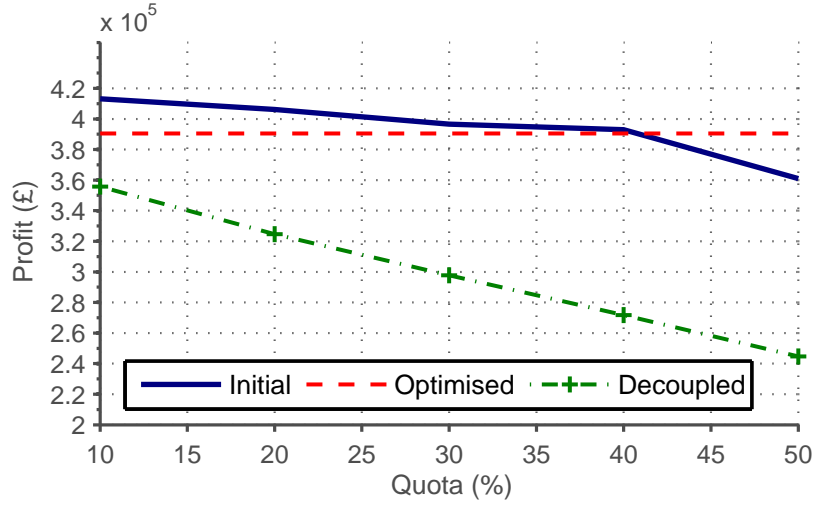


Figure 5.3: Decoupling profit in the presence of RES mandate.

reduces at higher quotas—to compensate for a lack of IPP capacity.

In terms of retail aspects, it is observed that decoupling removes the sales surplus. But it is important to also show the role of the surplus in line with DISCO incentives in the RSILCO model. The incentives are calculated as a percentage of the required revenue R_0 with

$$\mu_{\%}^{\text{eq}} = \frac{100(\mu^{\text{inc}} + \mu^{\text{ps}})}{R_0}, \quad (5.15)$$

adding the retail surplus gives

$$\mu_{\%}^{\text{eqs}} = \frac{100(\mu^{\text{inc}} + \mu^{\text{ps}} + \mu^{\text{sur}})}{R_0} \quad (5.16)$$

$$\mu^{\text{sur}} = \begin{cases} \mu_a + \mu_b - R_0, & \text{if } \mu_a + \mu_b \geq R_0; \\ 0, & \text{otherwise.} \end{cases} \quad (5.17)$$

The incentives can also be calculated as a percentage of the actual revenue, particularly the revenue obtained before the quota obligation is applied, which includes only the load change from the required case (5.18):

$$\mu_{\%}^{\text{act}} = \frac{100(\mu^{\text{inc}} + \mu^{\text{ps}})}{\mu_a + \mu_b}. \quad (5.18)$$

Fig. 5.5 shows the relative DISCO incentives obtained by the optimisation model ex-

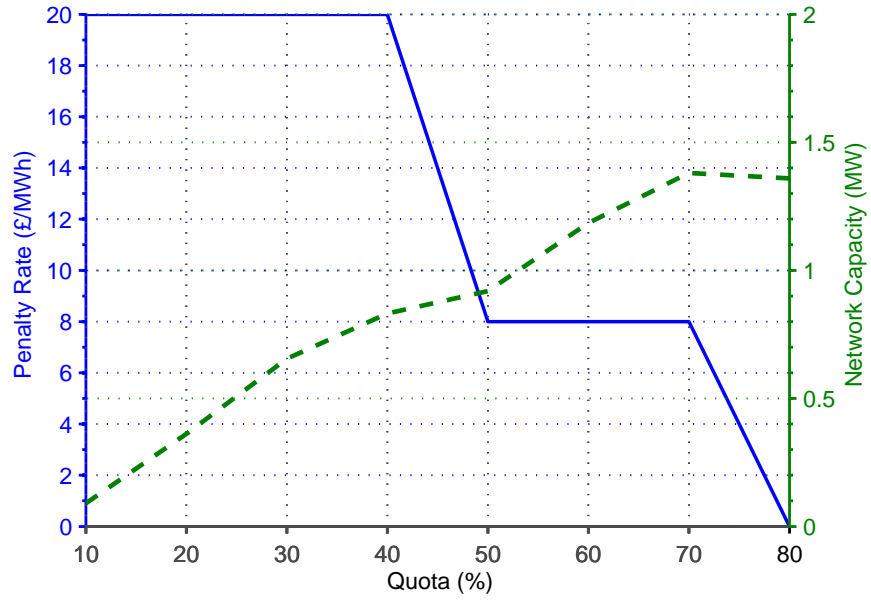


Figure 5.4: Quota penalty rate and corresponding network capacity for the optimised decoupling model.

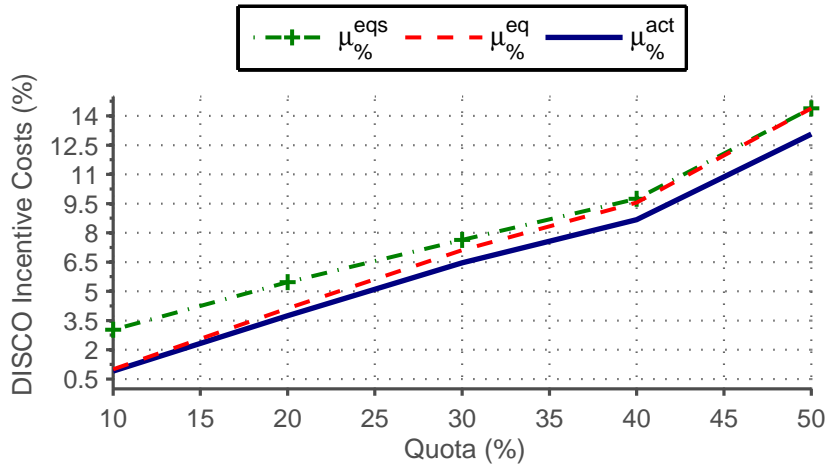


Figure 5.5: Costs of DISCO incentives (sum of cost recovery, discounted export payment and penalty saving) as percentage of retail revenue. $\mu_{\%}^{eq}$: excludes retail surplus. $\mu_{\%}^{eqs}$: includes retail surplus. $\mu_{\%}^{act}$: incentives as a share of actual revenue.

pressed as percentages. The incentives account for less than 5% of the retail revenue for quotas below 20% and over 14% for quotas in excess of 50%. The subsidising effect of the retail surplus fades with growing quota obligation. To make up for this shift incentives must be increased. Hence, the instances with and without the surplus eventually converge. Finally, because the minimum allowed IPP capacity exceeds the maximum capacity of the 69-bus network under study, the incentives inherently compensate for the lack of IPP capacity.

5.5.5 Network Operation

Consider the SG allocations for the 50% quota and 3% load decrease. As seen in Fig. 5.6, part of the load can be met locally and the rest with generation imported from the network. The net generation curves for bus-7 and bus-61 are markedly different. Indeed the net energy for SG is 200% at bus-7 and 48.6% at bus-61. The difference in demand at the two buses contributes to that of SG capacity. Of course technical constraints must be satisfied in all demand and generation conditions. The optimised model produces voltage levels within allowable limits (0.95 pu and 1.05 pu)—see Fig. 5.7 and Fig. 5.8 for the temporal voltage profiles at all buses. Since all loads are of the constant power type, higher bus voltages minimise losses.

Energy losses also represent a cost that can be reduced with targeted generation near the consumption sites. For all quotas considered the connection of RES results in lower energy losses compared to the zero generation case. Relative to this case, the example illustrated in Fig. 5.6 experiences loss savings of 42.71%. These energy cost savings have a role in reducing the costs of RES scheme costs, i.e., quota obligation, FiT and DISCO support.

It is envisaged that the RSILCO model will render the RA capable of calculating network-appropriate capacity and allowable costs to match predetermined RES targets. Besides tightening the budget constraint and depending on regulation preference, the regulated DISCO can be rewarded if it achieves higher than expected capacity within budget. Otherwise excess profit can be recouped through the decoupling mechanism (incentives/penalty adjustment).

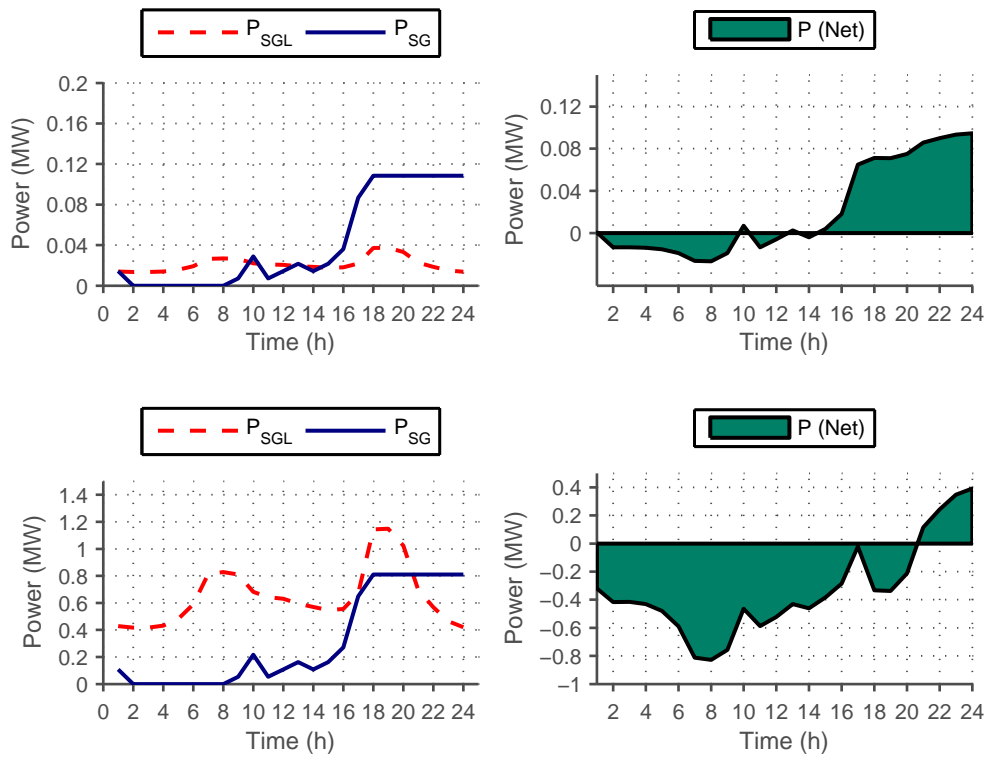


Figure 5.6: SG (generation and load) plots for bus-7 (top) and bus-61 (bottom). On the left, negative values denote imported power and positive values, exported power.

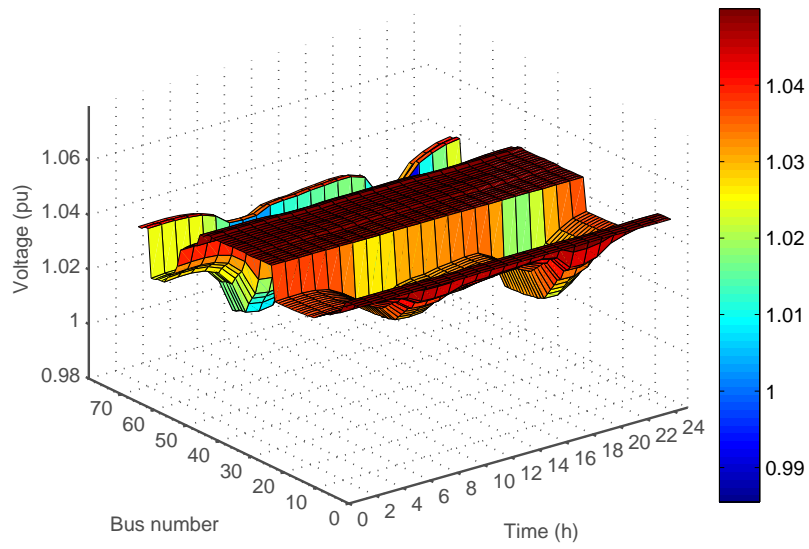


Figure 5.7: Voltage Profile of optimised model for 10% Quota.

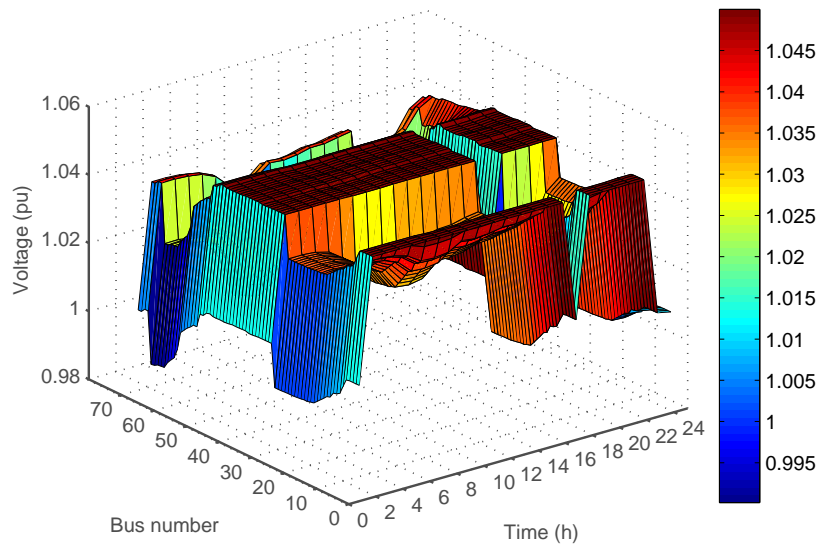


Figure 5.8: Voltage Profile of optimised model for 50% Quota.

5.6 Summary

This chapter developed the RSILCO model to provide the RA with the capability to promote targeted RES integration. The model neutralises the DISCO's bias or aversion to RES integration by minimising the impact on DISCO profits. In general, the costs of incentives depend on the strictness of the quota and the decision to enforce minimum SG. Given a specific quota, varied capacity can result as long as the costs are within budget. However, focusing solely on the profit impact (i.e. minimising profit deviation) can come at the expense of another objective—maximising RES capacity. One way to overcome the issue is to include the latter objective results in capacities that grow with quota specifications and cost allowances while instances of low capacity-high incentives are avoided.

The RSILCO model is shown to be superior to standard decoupling at preserving the DISCO's profit. Levels of energy use influence the location and capacity of RES, which in turn matches with suitable recovery rate, export rates and penalty. The sales surplus can to some extent offset the penalising effect of the quota obligations.

Chapter 6

Incentivising Active Network Operation

6.1 Introduction

The previous chapter described and quantified how DISCOs can be rewarded or penalised for their response to renewable DG targets. It introduced a model for network regulation, through which the profit of the DISCO is preserved in conditions of changing energy supply and consumption. This chapter addresses the role of regulation in promoting smart RES planning. The RES target-orientated RA aims to preserve DISCO profits, cap the cost to users and promote smart network operation. To this end the following problem emerges: given the RES targets, budget, network model, find suitable DG capacities, locations, incentives, and ANM operational guidance for the power network. This is a bilevel optimisation problem with minimisation of power curtailment cost at the lower level and minimisation of profit deviation at the higher level. The problem turns into a multilevel problem by introducing another operational objective - minimising the cost of energy losses through further ANM functionality, such as voltage and reactive power control.

6.2 Voltage and Reactive Power Control

This section is devoted to a concise description and numerical study of an active means of operating the network, namely, coordinated voltage and reactive power control or volt/var control (VVC). Here, the objective of VVC is to minimise energy loss and voltage deviations, thus improving the voltage quality along the network. The objective is achieved by coordinating the operation of OLTCs and capacitors. The periodic VVC problem is stated as (6.3.3):

$$\underset{u^t}{\text{minimise}} \quad \sum_{t=1}^{T_a} f(u^t, x^t), \quad (6.1a)$$

$$\text{subject to} \quad g(u^t, x^t) = 0, \quad \forall t \quad (6.1b)$$

$$h^- \leq h(u^t, x^t) \leq h^+, \quad \forall t \quad (6.1c)$$

$$\sum_{t=2}^{T_a} |u_{C,d}^t - u_{C,d}^{t-1}| \leq C^+ \quad (6.1d)$$

$$\sum_{t=2}^{T_a} |u_{\text{TAP}}^t - u_{\text{TAP}}^{t-1}| \leq u_T^+, \quad (6.1e)$$

The above model is governed by the nodal power balance, (6.1b); constraint (6.3.3b) defines the line flow and statutory voltage limits; (6.3.3c) and (6.3.3d) denote the switching effort of capacitors and OLTCs respectively.

Application to 69-bus Distribution System

The 69-bus PG&E distribution system shown in Fig. 4.6 is considered. Detailed data of the system can be found in [177]. Bus 1 is assumed to be connected to a transformer with reactance and resistance parameters of 1.923 Ω and 0.1923 Ω . Buses 6-27 are assigned Type A load profiles whereas nonzero load buses between bus 29 and bus 69 are represented by Type B profiles in Fig. 6.1. Two groups of capacitors are considered, the substation capacitor (SC), located at the substation and the feeder capacitors (FCs) connected along the feeders (FCs). There are 0.25 Mvar FCs installed at buses 19, 43 and 47. Buses 1, 58 and 66 each have one 0.3 Mvar capacitor.

In the base case, the SC and all the FCs remain switched on throughout the day.

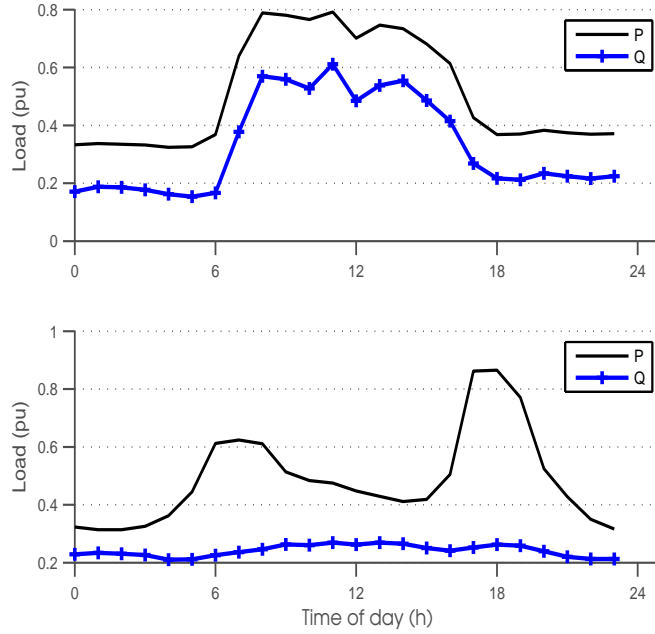


Figure 6.1: Daily load curves. Type A (top). Type B (bottom).

Table 6.1 provides operation interval results for all the capacitors on the network when the optimised VVC model (6.3.3) is employed. None of the capacitors exceed the permissible total (C^+) of 6. Overall, the highest number of operations is 4, produced

Table 6.1: Capacitor Operation Intervals for the 69-bus System

| Bus | On | Off |
|-----|--|---------------------------------|
| 1 | - | 00:00 - 00:00 |
| 19 | 08:00 - 00:00 | 00:00 - 08:00 |
| 43 | 00:00 - 10:00, 17:00 - 20:00, 22:00 - 00:00 | 10:00 - 17:00, 20:00 - 22:00 |
| 47 | 00:00 - 22:00 | 22:00 - 00:00 |
| 58 | 00:00 - 00:00 | - |
| 66 | - | 00:00 - 00:00 |

by the FC at bus 43. The total number of OLTC operations initiated by optimised VVC is 16, which is well below the limit u_T^+ of 30. Fig. 6.2 shows the maximum and minimum voltages at all buses over all time intervals. The lowest voltage for the base case is 0.9 pu at bus 64 and bus 65. With the application of optimised VVC the same bus experiences improved voltage management as the minimum observed voltage rises

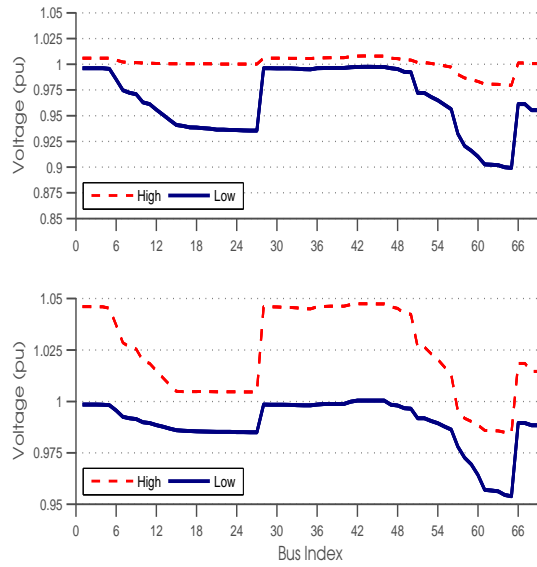


Figure 6.2: 69-bus system profile of lowest and highest voltages for the base case (top) and FVC-OSC (bottom) over 24 hours.

to 0.95 pu. In fact the total voltage deviation decreases to 0.5397, from 0.7780 in the base case. The total daily loss is reduced by 9% from 2.4589 MWh to 2.2374 MWh.

The above results demonstrate, in the presence of control resource limitations, that VVC can minimise losses and voltage deviations, while mitigating network constraints. The approach can therefore be employed as an operational tool to mitigate network constraint violations caused by RES integration.

6.3 Multilevel Active Incentive Optimisation

6.3.1 Regulation and Network Context

A primary aim of regulation is to facilitate a fair financial position for the DISCO and reward efficient operation of electricity networks. The RA has information about how DISCOs can operate networks efficiently. This requires the role of the DISCO to be taken into account when setting RES targets and cost caps.

When existing consumers begin to generate their own energy, the DISCO receives declining revenue at the retail price, but in reduced total units. Since the retail price is constituted by fixed and variable parts, the actual lost revenue must reflect the

unavoidable fixed part. This net revenue loss, μ_{nr} , defined as the actual revenue loss incurred by the DISCO when energy sales are lower than anticipated is:

$$\mu_{nr} = (N_{\text{sales}}^y - N_{\text{sales}}^{\text{ht}})(C^r - C^{\text{sac}}) \quad (6.2)$$

where N_{sales}^y are electricity units sold in year y ; $N_{\text{sales}}^{\text{ht}}$ are the electricity sales in a historical test year, used to determine the electricity price; C^{sac} is the short-run avoided cost of electricity generation. The net revenue loss represents fixed DISCO costs that are yet to be recovered. The costs include network infrastructure investment, O&M and staff costs. Here, the short-run avoided cost, C^{sac} is approximated by the wholesale electricity price, C^{W} .

6.3.2 Enabling Curtailment of SG and IPP

Only excess generation qualifies for curtailment at SG buses. Recall that $P_{k,t}^{\text{E}}$, the power difference between local load and generation at SG locations, is given by

$$P_{k,t}^{\text{E}} = P_{\text{SGL},k}^t - G_{\text{SG},k} \tilde{P}_{\text{SG},k}^t. \quad (6.3)$$

Whenever on-site load is higher than SG, $P_{k,t}^{\text{E}} > 0$, $P_{\text{SGL},k}^t = P_{k,t}^{\text{E}}$ and $P_{\text{SG},k}^t = 0$. Conversely, when on-site load is lower than SG, $P_{k,t}^{\text{E}} < 0$, $P_{\text{SGL},k}^t = 0$ and $P_{\text{SG},k}^t = P_{k,t}^{\text{E}}$. Total SG is then expressed as follows:

$$P_{\text{SG},k}^t = G_{\text{SG},k} \tilde{P}_{\text{SG},k}^t - P_{k,t}^{\text{E}} \alpha_{\text{SG},k}^t (u_{k,t}^{\text{e}} - 1), \quad (6.4)$$

$$0 \leq \alpha_{\text{SG},k}^t \leq 1, \quad (6.5)$$

where $u_{k,t}^{\text{e}}$ is the SG energy import or export status defined as

$$u_{k,t}^{\text{e}} = \begin{cases} 1, & \text{if } P_{k,t}^{\text{E}} \geq 0; \\ 0, & \text{otherwise.} \end{cases} \quad (6.6)$$

The IPP model is more straightforward,

$$P_{\text{IPP},i}^t = G_{\text{IPP},i} \tilde{P}_{\text{IPP},i}^t (1 - \alpha_{\text{IPP},i}^t), \quad (6.7)$$

$$0 \leq \alpha_{\text{IPP},i}^t \leq 1. \quad (6.8)$$

Since planning and operational decisions are made sequentially (find $G_{\text{IPP},i}$ then $\alpha_{\text{IPP},i}^t$), the expression on the right-hand side of (6.7) is linear in $\alpha_{\text{IPP},i}^t$ and equivalent to creating a new variable $P_{\text{IPP},i}^{\alpha,t}$, forming

$$P_{\text{IPP},i}^t = G_{\text{IPP},i} \tilde{P}_{\text{IPP},i}^t - P_{\text{IPP},i}^{\alpha,t}, \quad (6.9)$$

$$0 \leq P_{\text{IPP},i}^{\alpha,t} \leq G_{\text{IPP},i} \tilde{P}_{\text{IPP},i}^t. \quad (6.10)$$

Thus, the execution of curtailment within the proposed model is similar to that of [17] except that decisions here are driven by different objectives at two levels of optimisation. On this basis, a mathematical model to optimise the sharing of capacity between SGs and IPPs is developed in the following section.

6.3.3 Full Mathematical Formulation

This section presents the mathematical formulation of the RA, or central planning authority's perspective on, renewable SG and IPP allocation considering active network management. The key characteristics of the developed IPP and SG models are summarised in Table 6.2. A general overview of the proposed method is shown in Fig. 6.3. The intention of network planners is to determine desirable DG (SG and IPP) capacities and sites consistent with offered incentives, whereas network operators aim to minimise operational costs of generation. The two objectives are solved jointly, with the planning and operational problems at the upper and lower levels respectively. Referring to Fig. 6.3, it can be seen that the associative structure of the proposed method means that the calculations of all variables (e.g. capacity and curtailment) all influence one another. The framework can also accommodate VVC. The resulting formulation is a multilevel MINLP.

Table 6.2: Summary of developed IPP and SG models

| | IPP | SG |
|-----------------------------------|---|--|
| Energy flow | export | import, export |
| Energy purchase price | C^{rc}, C^W | C^G, C^{et} |
| Retail price | – | C^e |
| Size restriction | yes ($G_{SG,k}^{max} < G_{IPP,i} \leq G_{IPP,k}^{max}$) | no ($0 \leq G_{SG,k} \leq G_{SG,k}^{max}$) |
| Quota contribution | generation | load |
| Regulatory Control | quantity | price |
| Curtailement qualification | curtail full output | curtail exported output |
| Objective | min. compliance costs | min. revenue erosion |

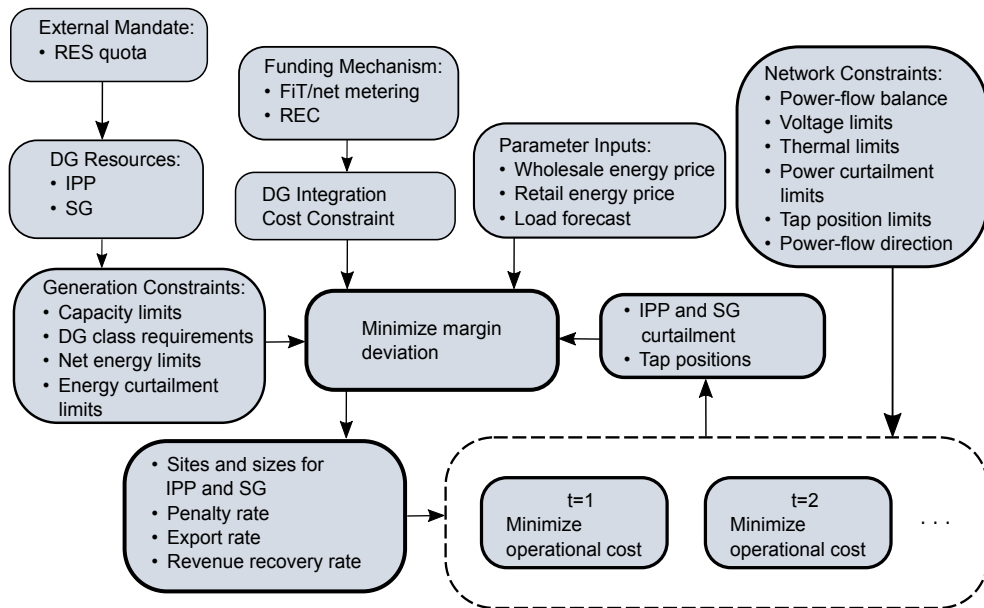


Figure 6.3: Proposed structure of the regulation optimisation model for DG location and capacity allocation in active networks. Here, t , denotes the operational time step.

The objective is to minimise deviation of the DISCO's profit from the baseline before DG integration.

$$\text{minimise } J_P = (J_D - J_Q) - J_C, \quad (6.11)$$

J_C is the profit baseline that must be maintained regardless of revenue or cost influences such as RES additions or load variations, J_Q is the penalty payment for renewable energy shortfall and J_D is the profit from the sale of energy and incentives for revenue loss and SG energy export. The penalty payment is required when total IPP capacity is lower than pre-specified quota, which is given as a percentage of the total energy delivered to consumers. Note that integration of SG reduces the absolute quota by decreasing the amount of energy required by consumers. The expression for calculating the penalty payment is

$$J_Q = \left(C^b \sum_{t \in T} \left(r^o \left(\sum_{d \in D} P_{L,d}^t - \sum_{k \in K} P_{SG,k}^t - \sum_{i \in I} P_{IPP,i}^t \right) \tau \right) \right) u_c. \quad (6.12)$$

Recall that the variable u_c indicates whether or not the DISCO complies with the quota obligation, as defined in (1). When the DISCO complies with this obligation for IPP integration, it only incurs the electricity costs represented by J_D . If the DISCO fails to fill the IPP quota the total cost becomes the sum of penalty payments and the wholesale cost. J_D , the second part of the objective function, is defined as

$$J_D = \mu_a - \mu_b + \mu_c - \mu_d + \mu_e, \quad (6.13)$$

where the different components are outlined below. A noteworthy difference between the formulation presented in Chapter 5 and that presented here is that the former considers passive network operation whereas the current formulation embeds optimised, temporal power curtailment. Indeed the operational layer makes it a much more challenging problem. This is clearly detailed in the following energy service functions and constraints.

Energy Service Functions

- a) μ_a : This is income from selling energy to all consumers on the network.
- b) μ_b : This function represents revenue loss due to reduced energy consumption at candidate SG locations. This function does not allow curtailment because it can only be non-zero when the SG is less than the associated local load. The loss of revenue caused by SG is proportional to the local generation level.
- c) μ_c : The DISCO purchases energy at the wholesale price, C^e from the substation and IPP to supply all loads not supplied by SG. This function represents the total wholesale energy cost. It depends among others on the values realised by curtailment variable $\alpha_{\text{IPP},i}^t$.
- d) μ_d : This function represents a revenue recovery mechanism, which is the proportion of the total revenue lost by introducing SG to the system. The cost component is recovered from ratepayers or through other means available to the DISCO for dealing with revenue erosion.
- e) μ_e : This function is the value the DISCO places on energy exported by SG. This amount is the DISCO's partial contribution to FiTs and is thus not recovered from ratepayers. If $C^{ee} = 0$ a saving in wholesale energy cost is realised, once the SG capacity rises to levels whereby generation exceeds demand. In contrast, $C^{ee} = C^W$ means the purchase rates of energy for SG, IPP and upstream sources are identical.

The full mathematical expression for J_D is given by

$$\begin{aligned}
 J_D = & \underbrace{C^r \sum_{t \in T} \sum_{d \in D} P_{L,d}^t \tau}_{\mu_a} + \underbrace{C^r \sum_{t \in T} \sum_{k \in K} P_{k,t}^E \tau u_{k,t}^e}_{\mu_b} \\
 & - \underbrace{C^e \sum_{t \in T} \left(P_s^t + \sum_{i \in I} G_{\text{IPP},i} \tilde{P}_{\text{IPP},i}^t (1 - \alpha_{\text{IPP},i}^t) \right) \tau}_{\mu_c} \\
 & + \underbrace{C^{rv} \sum_{t \in T} \sum_{k \in K} \left(G_{\text{SG},k} \tilde{P}_{\text{SG},k}^t u_{k,t}^e + P_{\text{SGL},k}^t (1 - u_{k,t}^e) \right) \tau}_{\mu_d}
 \end{aligned}$$

$$- \underbrace{C^{ee} \sum_{t \in T} \sum_{k \in K} P_{k,t}^E (1 - \alpha_{SG,k}^t) (u_{k,t}^e - 1)}_{\mu_e} \tau. \quad (6.14)$$

All financial variables, the recovery, export and penalty rates depend on the energy produced and consumed over all intervals. The same applies to the net energy and total energy curtailment. The objective function (6.11) is minimised along with power curtailment subject to the constraints described below.

6.3.4 Planning and Operational Constraints

- 1) *Support scheme budget.* This constraint limits the total cost of RES support to be recovered from customers. It consists of quota compliance costs, barring penalty costs; costs of FiT for all SG energy output and energy export. The power export costs depend on the DISCO incentive level. Null incentive ($C^{ee} = 1$) requires the DISCO to pay the full costs of energy export, whereas a maximum incentive ($C^{ee} = 0$) passes through the export costs to customers.

$$C^G \sum_{t \in T} \sum_{k \in K} P_{SG,k}^t + C^{et} \sum_{t \in T} \sum_{k \in K} P_{k,t}^E (1 - \alpha_{SG,k}^t) (u_{k,t}^e - 1) + C^{rc} \sum_{t \in T} \sum_{i \in I} P_{IPP,i}^t (1 - \alpha_{IPP,i}^t) + \mu_d - \mu_e \leq a_F. \quad (6.15)$$

- 2) *Target for self-generation.* The minimum SG constraint is described by (5.10). Although the requirement to integrate SG imposes no direct penalty, when a strict target is imposed, the DISCO guarantees network connection of smaller SG over the larger IPP. This constraint must not encroach heavily on the overall quota requirement. Thus, r^s is kept significantly lower than r^o .
- 3) *Minimum profit requirement:*

$$J_Q + J_D \geq J_C \quad (6.16)$$

- 4) *Net energy limits:* The total energy produced by SG is expressed in relation to local energy use over the evaluation period, permitting net consumers and net exporters. Hence, local energy production is limited according to (4.13).

5) *IPP and SG curtailment limits.* Two curtailment strategies are considered. The DG power output is restricted in every load-generation interval, and the total energy curtailment accumulates over time and is limited over the evaluation period. Of note, is the disparity between IPP and SG curtailment. All power produced by IPP is exported to the network. Whenever necessary the power output can be fully curtailed. Intuitively, SG output does not fully qualify for curtailment because some power is consumed locally. Therefore, only exported power is curtailed. In real cases, commercial arrangements, known as principles of access (described in subsection) must be followed to manage output of multiple DG plants. The model applied here is technical best, but other principles of access can be employed as described in [33]. The curtailment constraints are expressed as follows:

$$\sum_{t \in T} \alpha_{SG,k}^t \leq a_{ESk} \sum_{t \in T} G_{SG,k} \tilde{P}_{SG,k}^t, \quad (6.17)$$

$$\sum_{t \in T} \alpha_{IPP,i}^t \leq a_{EIi} G_{IPP,i} \sum_{t \in T} \tilde{P}_{IPP,i}^t. \quad (6.18)$$

$$\alpha_{IPP,i}^t \leq \alpha_{IPP}^{\max}, \quad (6.19)$$

$$\alpha_{SG,k}^t \leq \alpha_{SG}^{\max}, \quad (6.20)$$

$$P_{IPP,i}^{\min} \leq P_{IPP,i}^t (1 - \alpha_{IPP,i}^t) \leq P_{IPP,i}^{\max}, \quad (6.21)$$

$$P_{EXP,k}^{\min} \leq P_{k,t}^E (1 - \alpha_{SG,k}^t) (u_{k,t}^e - 1) \leq P_{EXP,k}^{\max}, \quad (6.22)$$

The actual power outputs of IPP and SG are functions of curtailment and must fall within its lower and upper bounds. The upper bound is computed in the upper-level problem.

6) *Nodal Power Balance:* The total power consumption must be equal to the total power supply at each bus as stated by Kirchhoff's current law, maintaining power-flow balance at the t th interval

$$P_{G,d}^t + G_{IPP,i} \tilde{P}_{IPP,i}^t (1 - \alpha_{IPP,i}^t) + P_{k,t}^E (1 - \alpha_{SG,k}^t) (1 - u_{k,t}^e) = P_{b,d}^t + P_{L,d}^t + P_{k,t}^E u_{k,t}^e \quad (6.23)$$

$$Q_{G,d}^t + Q_{IPP,i}^t(1 - \alpha_{IPP,i}^t) + Q_{k,t}^E(1 - \alpha_{SG,k}^t)(1 - u_{k,t}^e) = Q_{b,d}^t + Q_{L,d}^t + Q_{k,t}^E u_{k,t}^e \quad (6.24)$$

7) *Active and Reactive Branch Power Flows:*

$$P_{b,d}^t = V_d^t \sum_{j=1}^D V_j^t [G_{dj}^t \cos(\delta_d^t - \delta_j^t) + B_{dj}^t \sin(\delta_d^t - \delta_j^t)], \quad (6.25)$$

$$Q_{b,d}^t = V_d^t \sum_{j=1}^D V_j^t [G_{dj}^t \sin(\delta_d^t - \delta_j^t) - B_{dj}^t \cos(\delta_d^t - \delta_j^t)]. \quad (6.26)$$

8) *Capacity restrictions:* The separate SG and IPP capacity limits are enforced using (3.26) and (3.27), noting that

$$G_{SG,k}^{\max} < G_{IPP,i}^{\min}. \quad (6.27)$$

9) *Network limits:* The voltage, thermal loading and power-flow limits must satisfy (3.25), (3.28) and (3.29) at each bus must be within permissible levels at all times. Restricted power flows include those at the interfaces with adjacent networks. For networks with the capability to accommodate upstream flows, the restriction on the power flow direction can be removed.

Note that the net energy constraint, (4.13), imposes a limit on the SG capacity like the capacity constraint. This limit factors in the size of the load such that large loads will have higher limits compared to small loads. In contrast, the capacity constraint imposes the same limit irrespective of the size of the load. The final formulation takes the following form:

$$\underset{C^{rv}, C^{ee}, C^b, G_{IPP}, G_{SG,k}}{\text{minimise}} \quad J_P, \quad (6.28a)$$

$$\text{subject to} \quad (6.15) - (6.18), \quad (6.28b)$$

$$(3.26), (3.27), \quad (6.28c)$$

$$(4.13), \quad (6.28d)$$

$$\underset{P_{IPP,i}^t, P_{SG,k}^t}{\text{minimise}} \quad J_\phi, \quad (6.28e)$$

$$\text{subject to} \quad (6.19) - (6.26), \quad (6.28f)$$

$$(3.25), (3.28), \quad (6.28g)$$

$$(3.29). \quad (6.28h)$$

where is $J_\phi = \sum_{i \in I} c_2 P_{\text{IPP},i}^2 + c_1 P_{\text{IPP},i}$ for IPP at every time step t ; similarly, the quadratic function is employed for the set of SG. The coefficients are selected such that curtailed power is minimised.

6.3.5 Alternative Disjunction Models

Logical relationships increase the complexity of presented SG and IPP optimisation models. This section discusses various ways to model the logical relationships between variables. In the quota obligation mechanism the binary variable, u_c , can be removed by enforcing the constraint (6.29) and retaining the quota cost objective.

$$r^o \left(\sum_{d \in D} P_{L,d}^t - \sum_{k \in K} P_{\text{SG},k}^t \right) - \sum_{i \in I} P_{\text{IPP},i}^t \geq 0 \quad (6.29)$$

Alternatively, the penalty (compliance) formulation can be restructured using a continuous variable. This can be done by the following constrained formulation,

$$\text{minimise } z_c, \quad (6.30)$$

$$z_c \geq \left(C^b \sum_{t \in T} \left(r^o \left(\sum_{d \in D} P_{L,d}^t - \sum_{k \in K} P_{\text{SG},k}^t \right) - \sum_{i \in I} P_{\text{IPP},i}^t \right) \tau \right), \quad (6.31)$$

$$z_c \geq 0 \quad (6.32)$$

The constraints (6.31)–(6.32) hold simultaneously. When minimised, the variable z_c will approach zero with growing RES capacity, meaning the DISCO is in compliance with the quota requirement. When the calculated capacity is not in compliance, z_c will be higher but minimised. The above equations mimic the binary decision of quota compliance without over-compliance. That is, IPP must not exceed the imposed requirement. Obviously this constraint is restrictive if there is additional value for the DISCO (e.g. reduced losses) for accommodating excess DG.

Formulating the problem using mathematical programs with complementarity constraints (MPCCs) or equivalent mathematical programs with equilibrium constraints (MPECs) provides another continuous form solvable as NLP. Using the model Heaviside function, the penalty function is re-written as [182],

$$\sum_{t \in T} \left(r^o \left(\left(\sum_{d \in D} P_{L,d}^t - \sum_{k \in K} P_{SG,k}^t \right) - \sum_{i \in I} P_{IPP,i}^t \right) \tau (1 - u_c) = 0, \quad (6.33)$$

$$\sum_{t \in T} \left(r^o \left(\left(\sum_{d \in D} P_{L,d}^t - \sum_{k \in K} P_{SG,k}^t \right) - \sum_{i \in I} P_{IPP,i}^t \right) \tau \geq 0, \quad (6.34)$$

$$\sum_{t \in T} \left(r^o \left(\left(\sum_{d \in D} P_{L,d}^t - \sum_{k \in K} P_{SG,k}^t \right) - \sum_{i \in I} P_{IPP,i}^t \right) \tau = z_+^2 - z_-^2, \quad (6.35)$$

$$z_+ z_- = 0, \quad (6.36)$$

$$(z_+^2 + z_-^2) z_0 = 0, \quad (6.37)$$

$$z_+(1 - u_c) + z_0(1 - u_c) + z_-(u_c) = 0. \quad (6.38)$$

Other logical variables in the model, such as the energy import/export from SG, can be represented in the same manner. This method does, however, present some issues. First, this continuous representation requires more variables to be added to the model, which are not part of the original formulation. Second, ambiguity arises when the logical, and all the complementarity variables are zero concurrently. This affects feasibility—the strategy depends on an initial estimate (of z_0) to converge to feasible solutions [182–184]. In fact, MPECs do not comply with standard constraint qualifications including linear independence constraint qualification and Mangasarian-Fromovits constraint qualification at every feasible point [185]. This makes it difficult to suitably employ the established KKT optimality conditions. To better solve MPCCs requires special constraint conditions and modifications of standard NLP methods such as regularisation, smoothing and relaxation [186]. Finally, the product of continuous and logical variables can be reconstructed using the classical big- M technique [187]. But if the large scalar M is not carefully chosen it can cause numerical instability and result in low-quality bounds [188, 189].

6.3.6 Latent Capacity-Driven Penalty Strategy

It has been observed in Chapter 5 that the quota penalty may be too severe when the quota requirement exceeds the capacity of a constrained network. The extent of the capacity constraint is addressed here: specifically, how does the RA determine capacity inadequacy since there are now operational solutions that can unlock latency within existing networks.

Some studies rely on a different environmental compliance model to represent renewable quota obligation. The model in [190] enforces compliance with an inequality constraint. This in essence implies that non-compliance is prohibited and that the company complies strictly with the quota obligation. The environmental cost can also come in the form of an emissions penalty [58]. The fundamental difference between the quota and emissions penalties is that the quota scheme imposes a cost for non-RES generation above specific levels while the emissions penalty imposes a cost for all non-zero fossil-fuel generation. In some markets, alternative payments are favoured over strict penalties. Like REC costs, the costs of alternative payments are recovered from ratepayers. Although alternative payments serves as a ceiling for REC prices, they lead to increased energy costs with less renewable energy supply for customers.

In the proposed model, non-compliance is penalised, not prohibited. The penalty payment is proportional to the outstanding RES generation. REC markets are influenced by the way that regulatory authorities enforce environmental compliance. The compliance or penalty relaxation comes with conditions. In particular, the penalty mechanism requires that the DISCO maximises RES penetration and explores non-wires solution such as power curtailment, to release marginal network capacity. The optimisation strategy automatically updates the penalty, (6.39)-(6.40), when the network runs out of capacity headroom following exploration of ANM.

$$u^p := \text{sgn}^+(\Delta J_P - J_P). \quad (6.39)$$

$$r^o = r^{\max} u^p + (r^{\max} - \Delta r^o)(u^p - 1) \quad (6.40)$$

6.3.7 Coordinated Voltage Control Extension

In much the same manner as curtailment, VVC is incorporated as illustrated in Fig. 6.3. VVC seeks to remove voltage constraints by coordinating network resources while reducing operational costs by minimising losses. Since some networks consist of many control resources, a subset or full set of OLTCs or capacitors can be utilised. When there are many OLTCs, the relative value of each OLTC to VVC could be assessed in terms of its costs (e.g., maintenance and communication upgrade costs) and benefits (e.g., loss reduction and constraint removal).

6.4 Hierarchical IPM-PSO Algorithm

The context of the regulation problem requires that generation from RES matches the regulatory target, but curtailment be minimised. This is naturally conceptualised as a bilevel problem. In this case, a multi-period OPF represents the main problem at the second level. The objective function defines the cost of curtailment of both exported SG and IPP. OPF ensures that only minimum curtailment occurs, that is power produced by SG and IPP is at the maximum amount allowed by network constraints over every time interval. By passing the values of the integer transformer taps at each time step as inputs, the NLP structure of OPF formulation is maintained.

6.4.1 Bilevel Implementation

Bilevel, or more generally, multilevel problems are computationally demanding and can not be solved directly using mathematical optimisation algorithms. For bilevel problems, a single level transformation is usually preferred if the lower level problem can be represented by their equivalent formulations, such as the KKT conditions or primal-dual formulations [191, 192]. Linear bilevel programming has been proved to be NP-hard [193]. The complex nature of nonlinear bilevel programming implies that a reformulation is necessary to use deterministic methods. Alternatively, population-based methods can be employed, especially to solve nonconvex and non-differentiable functions [194].

The general representation of the bilevel problem under consideration is given by

$$\underset{x_u \in \Omega_U}{\text{minimise}} \quad F(x_u, x_L), \quad (6.41a)$$

$$\text{subject to} \quad G(x_u, x_L) \leq 0, \quad (6.41b)$$

$$\underset{x_l \in \Omega_L}{\text{minimise}} \quad f(x_u, x_l), \quad (6.41c)$$

$$\text{subject to} \quad g(x_u, x_l) \leq 0. \quad (6.41d)$$

The upper-level problem determines the sizing and locations of DG (IPP and SG) along with network incentives, i.e., recovery, export and penalty rates. The mid-level problem finds OLTC positions and the lower-level problem calculates curtailment levels for IPP and SG. The lower level problem is a level-constrained OPF (Table 6.4), which differs from the standard OPF (Table 6.3) by its multilevel variables and temporal constraints and variables. The corresponding objectives for each level are minimisation of profit deviation, losses, and DG curtailment. The whole problem is solved using the Hierarchical IPM-PSO algorithm.

Table 6.3: Notation for standard OPF

| Category | Standard OPF | Description |
|------------------------|------------------|---|
| Control variables | u | Power generation |
| State variables | x | Voltage magnitude and angle |
| Objective function | $\min f(u, x)$ | Minimise operational cost |
| Equality constraints | $g(u, x) = 0$ | Power flow equations |
| Inequality constraints | $h(u, x) \leq 0$ | Limits on generation, thermal branch flows and bus voltages |

6.4.2 Operating Scenario Reduction

The purpose of scenario reduction is to minimise the computational effort in power system studies. In analyses involving power flow calculations, loading and generation scenarios tend to be many, due to the temporally variable nature of different types of demand and generation. In networks with no RES, planning studies only required a small number of scenarios to account for network conditions over long periods of time. Studies specifically focused on worst cases, i.e., peak loading conditions, as the basis

Table 6.4: Notation for level-constrained OPF

| Category | LC-OPF | Description |
|--------------------------------------|--|---|
| Control variables | $u_{\text{SG}}^t, u_{\text{IPP}}^t$ | Site, capacity and time varied power generation |
| State variables | x^t | Site, capacity and time varied voltage magnitude and angle |
| Intertemporal variables | σ^t | Energy curtailment |
| Objective function | $\min. f(u_{\text{SG}}^t, u_{\text{IPP}}^t, x^t, \sigma^t)$ | Minimise operational cost for all time intervals |
| Equality constraints | $g(u_{\text{SG}}^t, u_{\text{IPP}}^t, x^t, \sigma^t) = 0$ | Temporal power flow equations with varying site and capacity |
| Interval inequality constraints | $h(u_{\text{SG}}^t, u_{\text{IPP}}^t, x^t, \sigma^t) \leq 0$ | Generator limits change with capacity and site; Voltage and thermal limits remain fixed |
| Intertemporal inequality constraints | $s(u_{\text{SG}}^t, u_{\text{IPP}}^t, x^t, \sigma^t) \leq 0$ | Total energy curtailment over the optimisation horizon is restricted |

Algorithm Overview Hierarchical IPM-PSO

- Step 0.** Initialisation:
- 0a.** Generate random positions and velocities for the initial particle population. Each particle must be within practical limits and comprises $G_{\text{IPP},i}$, $G_{\text{SG},k}$, u_i , C^{rv} and C^{ee} .
- 0b.** Set C^{b} equal to its upper limit.
- Step 1.** For all particles:
- Step 2.** Calculate $u_{k,t}^{\text{e}}$ and u_{c} .
- Step 3.** Given $G_{\text{IPP},i}$, $G_{\text{SG},k}$, solve the periodic OPF for all $t = 1, 2, \dots, T$ using the interior-point method. This step provides $P_{\text{IPP},i}^t$, $P_{\text{SG},k}^t$, $P_{d,j}^t$, $Q_{d,j}^t$ and V_d^t .
- Step 4.** Evaluate fitness function.
- Step 5.** Calculate C^{b} .
- Step 6.** Compare the current particle value with its pbest. Select best value among all particles' pbest values and set it as gbest value.
- Step 7.** End For.
- Step 8.** Termination criterion. While iteration count, $n_{\text{iter}} < n_{\text{iter}}^{\text{max}}$, go to Step 9; otherwise, stop.
- Step 9.** Update the inertia weight, particle velocities and positions. Go to Step 1.
-

for network improvements [28]. The emergence of more accurate switched capacitor sizing and energy loss analyses necessitated more scenarios [195, 196]. The additional scenarios can follow load duration curves, which provide typical load levels and their relative time durations derived from annual profiles [46].

For network integration of RES, planners widely use two scenarios, maximum demand - minimum generation and minimum demand - maximum generation scenarios. More detailed methods preserve demand-generation coincidence and chronological order. An accurate but computationally intensive method follows the time series of demand and generation, enabling the study of every operating condition [197]. As a result, the number of scenarios over a period of, say, one year would be a considerable 8760 using a scenario interval of one hour. Variable generation can also be considered by exploiting similarities in granular data through load-generation correlation and clustering [17]. This method begins with discretised loading and generation levels for many time steps for an extended period of time, e.g., one year. The data are reduced to a smaller set according to matched demand and generation pairs and corresponding durations. Other methods explicitly use statistical techniques to achieve characteristic and uncertain load and generation combinations [198].

Another way to incorporate the pattern of demand and generation is to use representative daily profiles. The advantage of representative profiles is that many load and generation curves can be handled without the need for detailed preprocessing. This is achieved by selecting days of the year for each profile, which coincide with highest net power injection and consumption for a given network. This depends on where the aggregation occurs. Higher level aggregation can miss local peaks and, in turn, constraints. Alternatively, the representative profiles of load and generation can be selected independently yielding highest total power supplied and sunk by individual or localised groups of generators and loads. Its shortcoming is that it considers scenarios that may never arise in reality if the worst conditions for load and generation do not coincide for the designated number of periods. In some cases it is possible to reduce data requirements of representative profiles on the basis of methods such as time interval clustering [199]

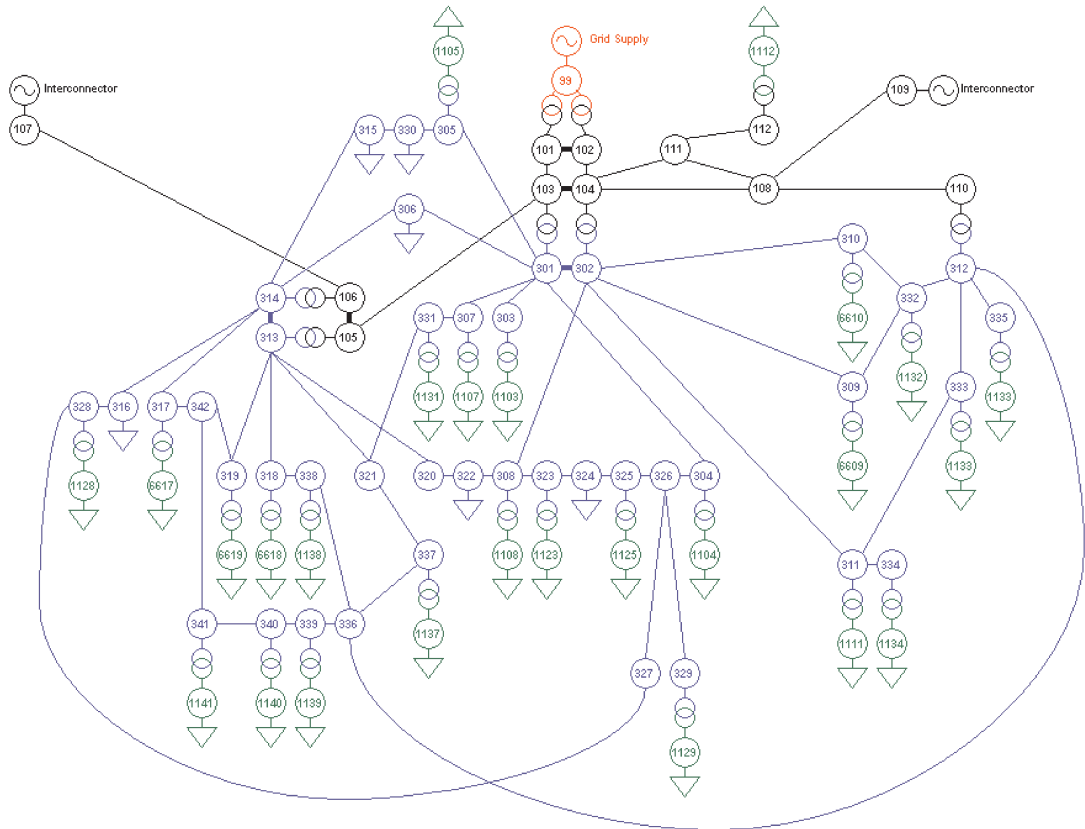


Figure 6.4: Line diagram of the UKGDS-EHV4 system.

6.5 Application to UKGDS

This section presents the test network and other input data utilised to test the bilevel, active regulation model to promote DG integration in active networks. An analysis of the performance of the model subsequently follows within the given context.

6.5.1 Test System Description

Fig. 6.4 shows the UKGDS-EHV4 system on which the experiments are run. The complete data for the system are available in [200], [201]. The system consists of twelve 132-kV buses, forty-two 33-kV buses, twenty-one 11-kV buses and five 6.6-kV buses.

Exports through the grid supply point (GSP) and interconnectors are restricted

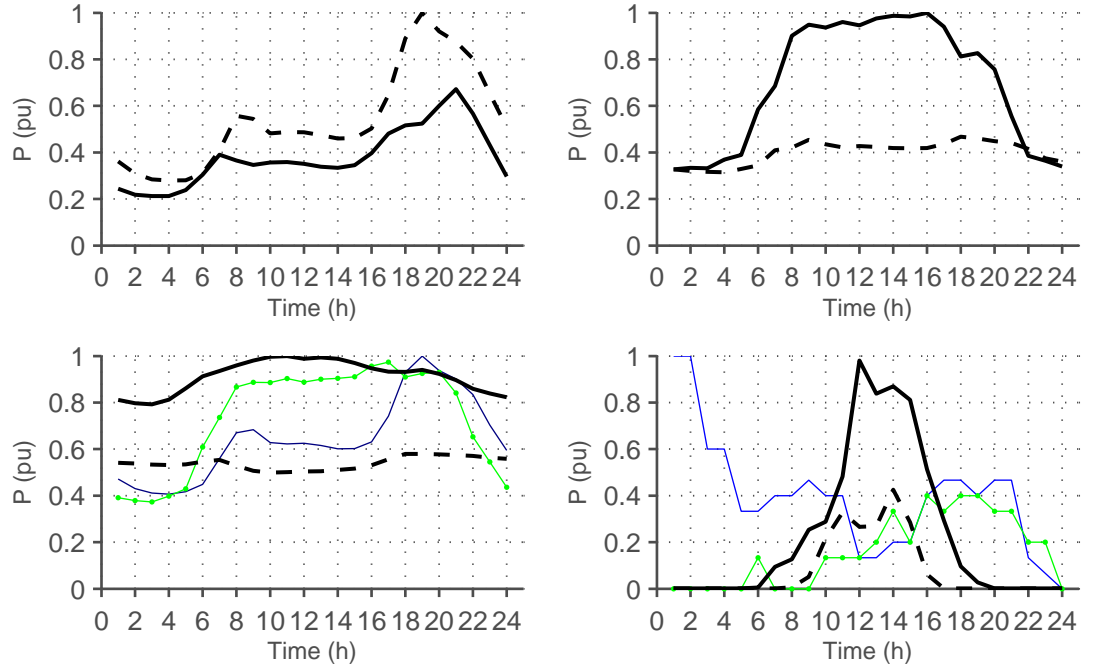


Figure 6.5: Normalised load profiles for different types of load and generation. Top left: residential load. Top right: commercial load. Bottom left: industrial (blue + green) and mixed (black) loads. Bottom right: PV (black) and wind generation (blue + green).

using the following constraints:

$$0 \leq P_{\text{gsp}} \leq P_{\text{gsp}}^{\text{max}} \quad (6.42)$$

$$0 \leq P_{\text{int1}} \leq P_{\text{int1}}^{\text{max}} \quad (6.43)$$

$$0 \leq P_{\text{int2}} \leq P_{\text{int2}}^{\text{max}} \quad (6.44)$$

Solar PV SG candidate sites are located at buses 1105, 1129 and 6618. Wind IPP candidate buses are 112, 312 and 319. In the demand-only scenario, the transformer secondary buses all have a target voltage of 1.025 pu. The demand-only scenario has an annual energy intake of 753.68 GWh and energy losses amounting to 1.278%. Fig. 6.5 shows a set of representative profiles that capture generation and demand variations. The load profiles for the residential, commercial and industrial load classes are derived

Table 6.5: Demand types

| Type | Residential | Commercial | Industrial | Mixed |
|------------|-------------------------------|-------------|----------------|-------|
| Bus number | 1104, 1105, 1108, 1111, 1123, | 6609, 6610 | 306, 315, 316 | 1112 |
| | 1125, 1128, 1129, 1132, 1133, | 6617, 6618, | 322, 324, 330, | |
| | 1134, 1135, 1137, 1138, 1139, | 6619 | 1103, 1107, | |
| | 1140, 1141 | | 1131 | |

from energy demand data of existing facilities [202, 203]. The industrial load data is based on Southern California Edison’s load profile of a facility consuming more than 500 kW at a voltage level above 2 kV and below 500 kV [203]. The residential loads have a load factor of 0.460, commercial loads, 0.547, and industrial loads, 0.726. The segmentation of loads into the different sectors is as follows: 41.3% residential, 14.8% commercial, 12.6% combination of commercial and residential, and 31.3% industrial. The demand types and locations are shown in Table 6.5. The load density is distributed across three voltage levels as follows: 0.14, 0.71, 0.15 for 33 kV, 11 kV, 6.6 kV levels respectively. The profiles for two non-consecutive days portraying PV power highest and lowest injection are shown in Fig. 6.5 (bottom right). The profiles are derived from the total production of an existing DG facility for the period between 2010 and 2016, giving a capacity factor of 0.159 [204]. Wind profiles in Fig. 6.5 are also utilised, yielding a capacity factor of 0.273 [205]. The normalised wind and PV profiles are multiplied by the generation capacity to obtain the power output for every interval.

Choice of Parameters

The ANC is set to 35%. To constrain energy curtailment, the allowed energy curtailment is limited to 10%. However, full power is allowed to be curtailed, as necessary, in a given time interval. If the penalty rate is conditionally adjusted, it is allowed to decline at a rate of 4 £/MWh. Curtailment in real networks varies substantially depending on the type of network, RES levels and constraints. It has been reported to be around 1% of total generation in some regions and in excess of 10% in others [206]. Here, the curtailment limit is set at 10% of total generation at every IPP site, and

Table 6.6: Input parameter values for study of regulation model

| | |
|---|----------------|
| Wholesale price of electricity (C^e) | 50 £/MWh |
| Retail price of electricity (C^r) | 75 £/MWh |
| Maximum penalty rate for non-compliance (C^b) | 20 £/MWh |
| Maximum revenue recovery rate (C^{rv}) | $0.5C^r$ £/MWh |
| Maximum DISCO energy export rate (C^{ee}) | $0.5C^e$ £/MWh |
| SG net energy limit (a_L) | 200% |
| IPP quota (r^o) | 10 - 40% |
| Minimum size of IPP (G_i^{\min}) | 3 MW |

likewise for exported generation at every SG site. Other input parameter values are shown in Table 6.6.

6.5.2 Numerical Results and Discussion

Some of the main features of the active regulation optimisation model are evaluated here. The numerical experiments include constrained financial resources and different generation permutations.

Limited Budget

Fig. 6.6 presents available funds and actual costs for three funding arrangements. For each budget the RES quota is adjusted from 10% to 40%. The costs are below budgeted amounts in all scenarios. But an additional measure must be taken at the highest quota and lowest budget. When the quota reaches 40%, for Budget C, the penalty rate drops to 8 £/MWh. This observation suggests that under a limited budget the RA can still relax the penalty to match minimum possible generation allocation at its preferred RES quota.

The relationship between the quota requirements and total allocated network capacity is plotted in Fig. 6.7. As the quota requirement approaches 40%, the model is able to push the allocated capacity higher by applying more curtailment. But as the budget is lowered it becomes difficult to meet the quota. Hence the penalty payment is reduced in order to maintain the DISCO profit.

Branch flows, bus voltages and reverse power flows remain within limits. SG does

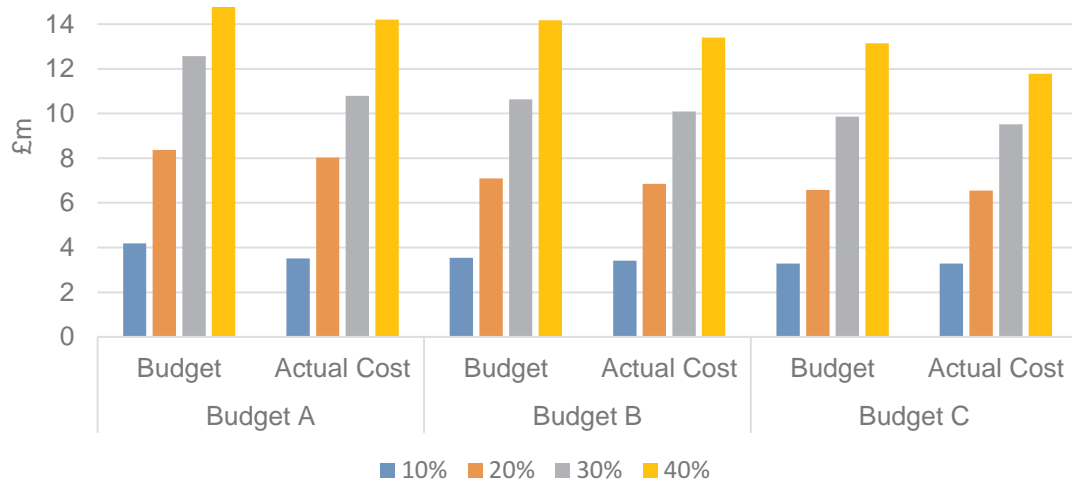


Figure 6.6: Budget allocation and actual costs for quota variations up to 40%. Budget A > budget B > budget C.

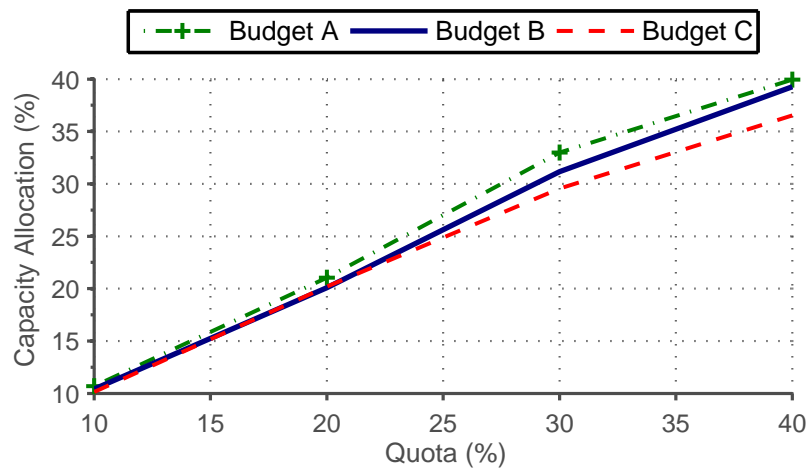


Figure 6.7: Actual capacity allocation for rising quota requirements.

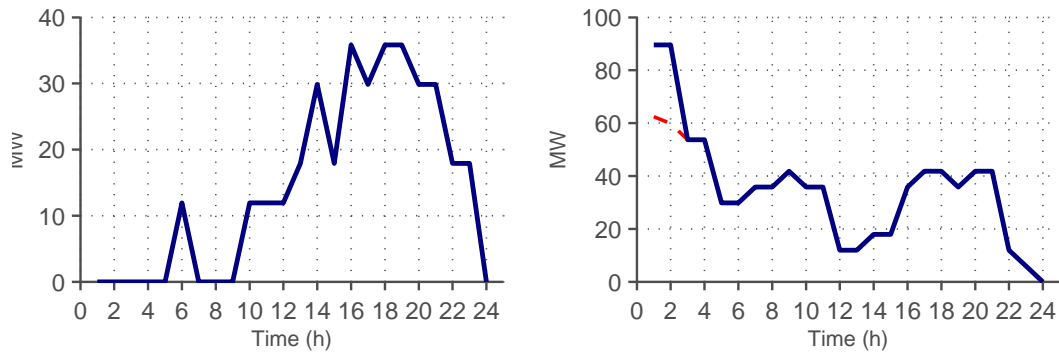


Figure 6.8: Potential generation (blue) and actual generation (red) profiles of IPP at bus-112 for 30% quota and 4% minimum SG.

not experience curtailment in any of the scenarios. This is because it is, at all times, lower than local demand.

Under the lowest budget SG is extremely restricted, accounting for little over 0.5% of total generation, making IPP the more dominant resource. This implies that budget minimisation displaces SG in order to preserve an acceptable profit level. Next the impact of enforcing a minimum SG requirement is quantified.

Minimum SG Requirement

A minimum requirement is imposed on the total SG within the network. Of particular focus are cases in which all SG must be at least 2 – 4% of the total energy consumed by the network.

Total generation from SG and IPP exceeds quota specifications only slightly. Minimum SG requirements are met, but at increased total costs compared to cases without mandated SG requirements. Relative to local load, net generation from SG is considerable at bus-1105, reaching the upper bound of 200% when the quota is 20% or lower. At the remaining buses net generation consistently stays well below 100%.

Notable observations can be made for the 30% quota and 4% minimum SG instance. Fig. 6.8 captures the IPP profile at bus-112. At the GSP (bus-99), the shape of the generation profile shown in Fig. 6.9 illustrates the aggregated effect of generation within the network. The lowest generation level is bounded by the reverse power flow constraint, which is the reason for IPP curtailment. The generation profiles of

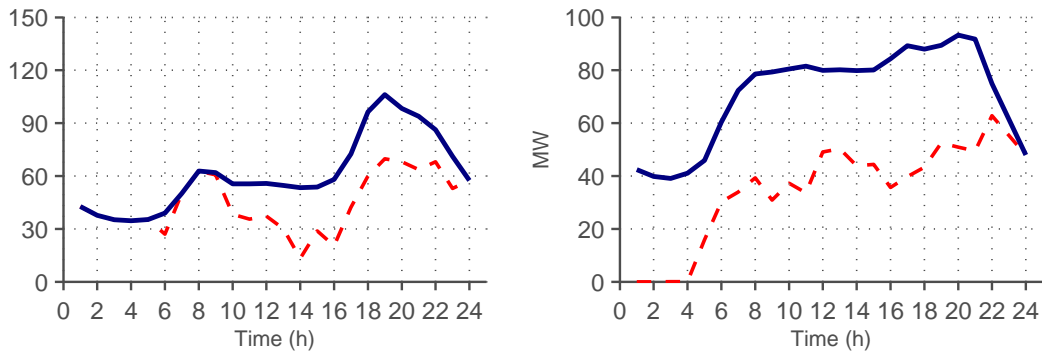


Figure 6.9: Zero quota GSP generation (blue) and actual GSP generation (red) profiles of IPP at 30% quota and 4% minimum SG.

SG at bus-1129 and bus-6618 are plotted in Fig. 6.10. Bus-1129 SG is curtailed at a time when it is exporting power and exceeding the 10 MVA loading limit of the local transformer (see Fig. 6.11). It is worth pointing out that flows are not restricted by the reverse power flow limit as is the case at the GSP and interconnections.

The curtailment strategy can be tested against that of the standard OPF. Suppose there exists another 15 MW independent generator at bus-6618, which, at times, contributes to overload of the transformer between bus-318 and bus-6618. The transformer has a loading limit of 10 MVA.

Running the standard OPF computation while neglecting the link between SG and local load yields the profiles in Fig. 6.12. It is clear that the curtailment action by standard OPF is not able to discriminate between generator sites. SG at bus-6618 is curtailed even though local demand, is at all times, higher than local generation. Indeed the decision to curtail local generation is, in this case, not feasible. By comparison, including SG in the nodal power balance equations in OPF as in (6.23) and (6.24) yields the profiles in Fig. 6.13. Only the independent generator experience curtailment because the SG site does not export any of its generation.

Note that reducing the net generation limit to 100% is similar to the higher generation limit instance in that SG capacity remains low for all quota variations. When the 4% minimum SG bound is imposed, SG capacity is raised up to the acceptable amount.

The properties of SG can be further understood with two load-generation metrics, self-consumption and self-sufficiency. The general definitions set out in [207] apply, but

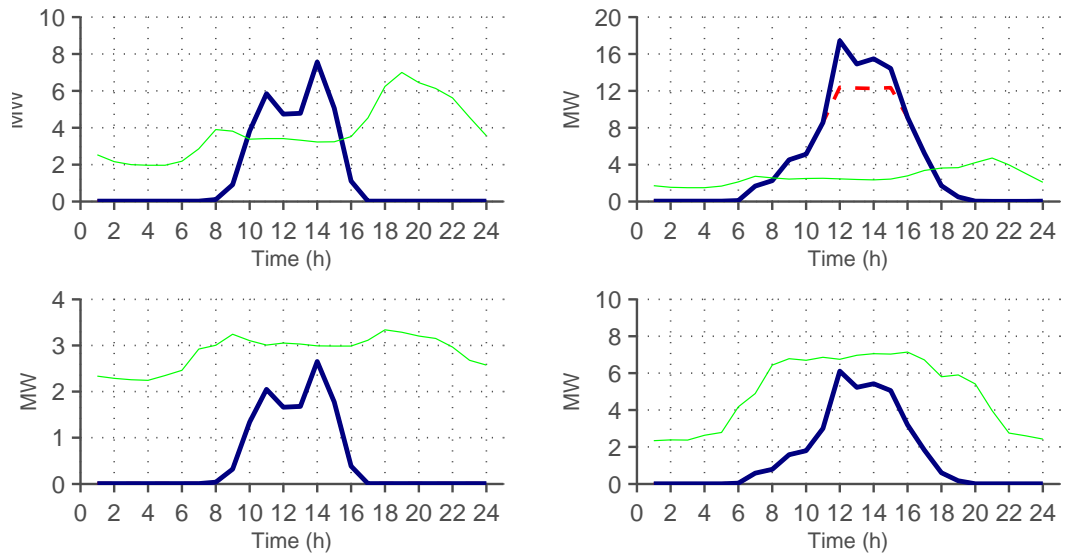


Figure 6.10: SG load (green), potential generation (blue) and actual generation (red) profiles at bus-1129 (top) and bus-6618 (bottom) for 30% quota and 4% minimum SG.

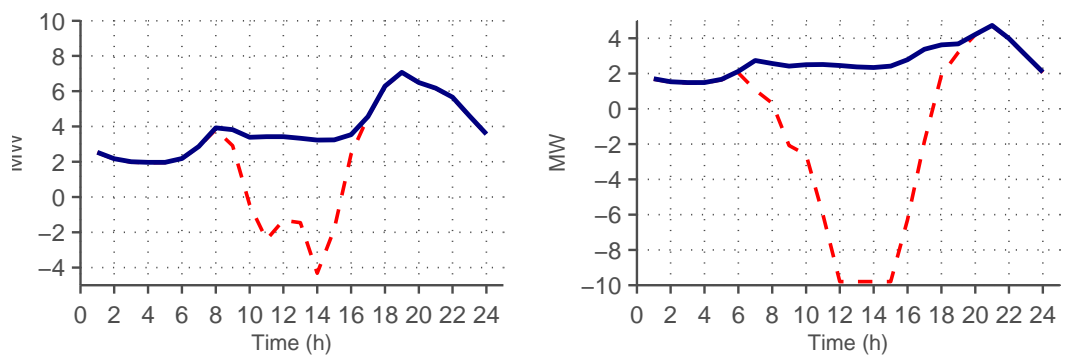


Figure 6.11: Zero quota transformer flow (blue) and actual transformer flow (blue) at 30% quota and 4% minimum SG. Negative values indicate a change power-flow direction.

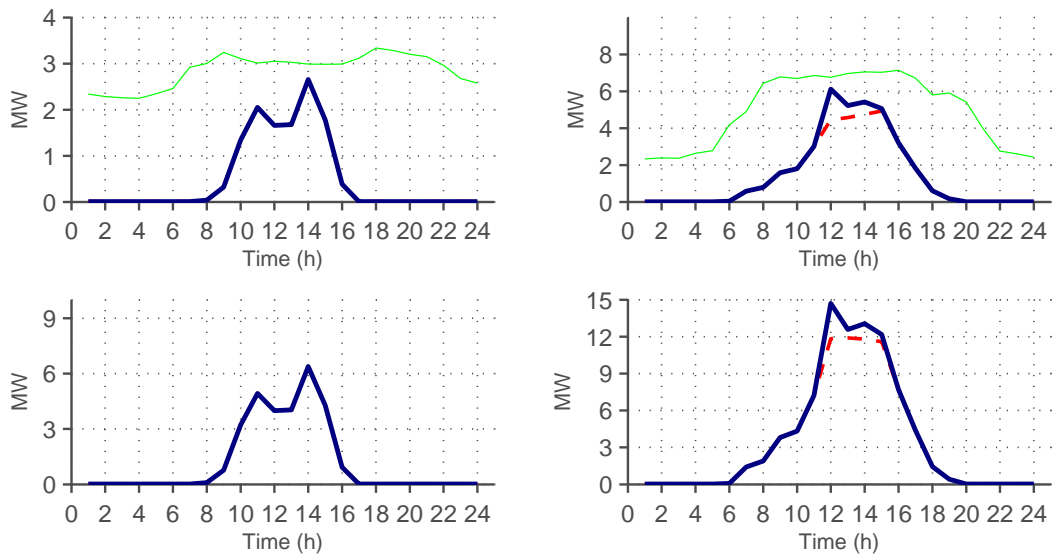


Figure 6.12: Load (green), potential generation (blue) and actual generation (red) profiles resulting from standard OPF. Joint generation and load profile for SG site (top). Generation profiles for a independent generation (bottom).

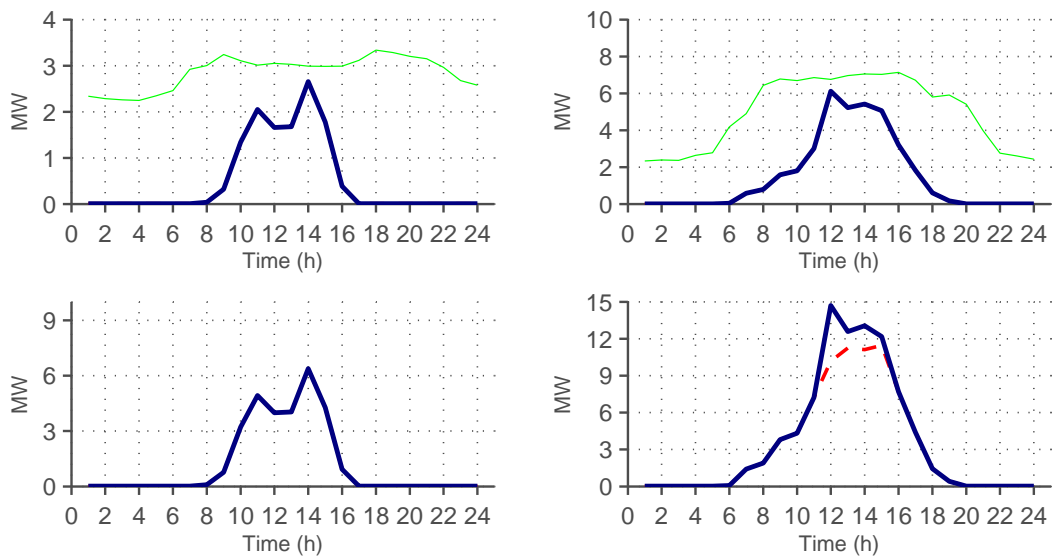


Figure 6.13: Load (green), potential generation (blue) and actual generation (red) profiles resulting from OPF using (6.23) and (6.24). Joint generation and load profile for SG site (top). Generation profiles for a independent generation (bottom).

Table 6.7: Generation capacity and financial impact relative to varying RES quota

| | 2% Min SG | | | | 4% Min SG | | | |
|----------------------|------------------|-------|--------|--------|------------------|-------|--------|--------|
| | 10% | 20% | 30% | 40% | 10% | 20% | 30% | 40% |
| Bus-112 IPP (MW) | 0.00 | 0.00 | 0.00 | 128.08 | 18.34 | 0.00 | 89.56 | 0.00 |
| Bus-312 IPP (MW) | 29.39 | 57.65 | 54.83 | 0.00 | 0.00 | 0.00 | 0.00 | 55.94 |
| Bus-319 IPP (MW) | 0.00 | 0.00 | 37.78 | 0.00 | 0.00 | 60.30 | 0.00 | 64.37 |
| Bus-1105 SG (MW) | 2.43 | 2.43 | 0.07 | 1.36 | 2.43 | 2.43 | 0.00 | 1.70 |
| Bus-1129 SG (MW) | 8.46 | 0.44 | 12.03 | 4.07 | 3.45 | 0.00 | 17.77 | 7.88 |
| Bus-6618 SG (MW) | 0.00 | 8.17 | 1.22 | 7.30 | 16.60 | 21.25 | 6.24 | 17.39 |
| Total DG (MW) | 40.27 | 68.68 | 105.93 | 140.81 | 40.81 | 83.97 | 113.57 | 147.29 |
| Recovery rate (pu) | 1.00 | 0.95 | 1.00 | 1.00 | 1.00 | 1.00 | 0.58 | 1.00 |
| Export rate (pu) | 0.00 | 1.00 | 0.00 | 0.98 | 1.00 | 0.00 | 1.00 | 0.00 |
| Penalty rate (£/MWh) | 20.00 | 20.00 | 20.00 | 16.00 | 20.00 | 20.00 | 20.00 | 8.00 |
| Budget (£m) | 4.64 | 7.92 | 11.21 | 14.50 | 5.99 | 9.28 | 12.56 | 15.85 |
| Actual cost (£m) | 4.63 | 7.91 | 11.17 | 14.42 | 5.79 | 9.19 | 12.30 | 15.50 |
| Penalty cost (£m) | 0.04 | 0.17 | 0.12 | 0.20 | 0.55 | 0.10 | 0.17 | 0.15 |
| Quota cost (£m) | 3.10 | 6.02 | 9.26 | 12.17 | 1.93 | 6.02 | 8.99 | 11.55 |
| SG cost (gen., £m) | 0.97 | 0.98 | 1.18 | 1.13 | 1.99 | 2.00 | 1.98 | 2.39 |
| SG cost (export, £m) | 0.35 | 0.15 | 0.40 | 0.11 | 0.57 | 0.73 | 0.65 | 0.72 |
| SG cost (total, £m) | 1.32 | 1.13 | 1.58 | 1.24 | 2.56 | 2.74 | 2.63 | 3.11 |
| Actual profit (£m) | 48.04 | 48.04 | 48.04 | 48.04 | 48.04 | 48.04 | 48.04 | 48.04 |

the metrics are constructed in the form that subscribes to the proposed optimisation formulation. Self-consumption refers to the share of total generation consumed within a SG site:

$$SC_{SG} = \frac{\sum_{t \in T} P_{SG,k}^t u_{k,t}^e + \sum_{t \in T} P_{SGL,k}^t (1 - u_{k,t}^e)}{\sum_{t \in T} P_{SG,k}^t}, \quad (6.45)$$

self-sufficiency defines the share of total load that is self-supplied,

$$SS_{SG} = \frac{\sum_{t \in T} P_{SG,k}^t u_{k,t}^e + \sum_{t \in T} P_{SGL,k}^t (1 - u_{k,t}^e)}{\sum_{t \in T} P_{SGL,k}^t}. \quad (6.46)$$

Table 6.7 shows the financial impact and specific bus capacities and Table 6.8 the corresponding values of generation measures including self-consumption and self-sufficiency. There is no dominant trend in respect of any of these SG factors because only the capacity and net energy are constrained in the optimisation model. This points to the

Table 6.8: Generation measures of IPP and SG relative to varying RES quota

| | 2% Min SG | | | | 4% Min SG | | | |
|--------------------------------------|------------------|--------|-------|--------|------------------|--------|-------|--------|
| | 10% | 20% | 30% | 40% | 10% | 20% | 30% | 40% |
| Generation (%-network load) | | | | | | | | |
| IPP | 9.61 | 18.69 | 28.74 | 37.78 | 6.00 | 18.69 | 27.89 | 35.84 |
| SG | 2.03 | 2.06 | 2.49 | 2.38 | 4.20 | 4.21 | 4.17 | 5.02 |
| Total | 11.64 | 20.75 | 31.22 | 40.16 | 10.19 | 22.90 | 32.06 | 40.86 |
| Net Generation (%-local load) | | | | | | | | |
| 1105 | 200.00 | 200.00 | 5.48 | 112.01 | 200.00 | 200.00 | 0.00 | 140.06 |
| 1129 | 41.65 | 2.16 | 59.26 | 20.03 | 16.98 | 0.00 | 79.17 | 38.83 |
| 6618 | 0.00 | 33.18 | 4.94 | 29.66 | 67.42 | 81.76 | 25.33 | 70.24 |
| Energy Curtailment (%) | | | | | | | | |
| Bus-112 IPP | 0.00 | 0.00 | 0.00 | 9.80 | 0.00 | 0.00 | 4.76 | 0.00 |
| Bus-312 IPP | 0.00 | 0.85 | 6.73 | 0.00 | 0.00 | 0.00 | 0.00 | 7.98 |
| Bus-319 IPP | 0.00 | 0.00 | 2.77 | 0.00 | 0.00 | 5.24 | 0.00 | 9.72 |
| Bus-1105 SG | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bus-1129 SG | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 9.57 | 0.00 |
| Bus-6618 SG | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 5.28 | 0.00 | 0.58 |
| Self-Consumption | | | | | | | | |
| Bus-1105 SG | 0.19 | 0.19 | 1.00 | 0.31 | 0.19 | 0.19 | 0.00 | 0.26 |
| Bus-1129 SG | 0.63 | 1.00 | 0.52 | 0.85 | 0.91 | 0.00 | 0.38 | 0.66 |
| Bus-6618 SG | 0.00 | 0.97 | 1.00 | 0.99 | 0.65 | 0.55 | 1.00 | 0.63 |
| Self-Sufficiency | | | | | | | | |
| Bus-1105 SG | 0.38 | 0.38 | 0.05 | 0.35 | 0.38 | 0.38 | 0.00 | 0.36 |
| Bus-1129 SG | 0.26 | 0.02 | 0.31 | 0.17 | 0.15 | 0.00 | 0.34 | 0.25 |
| Bus-6618 SG | 0.00 | 0.32 | 0.05 | 0.29 | 0.44 | 0.47 | 0.25 | 0.44 |

ability of the proposed model to accommodate diverse SG characteristics by tailoring recovery and export rates in tandem to minimise the profit impact. All instances of curtailment respect the illustrative limit of 10%. Note that because limited curtailment is allowed as long as the result minimises profit deviation, curtailment occurs even at lower quotas. If this not be desirable in practice, the result can easily be avoided by setting the maximum curtailment to zero for lower quotas.

6.6 Summary

This chapter presented the regulation model for renewable, SG and IPP capacity and location allocation in networks allowing ANM in the form of power curtailment. The

allocation admits an operational layer and the resulting form of regulation emerges as a bilevel optimisation problem. Numerical results demonstrate that the capability of networks to accommodate increased RES can be determined without assumptions on predetermined generation levels. For a given network the proposed optimisation model only requires network information (including bounds on variables) and policy goals to assist important decisions affecting RES access to network capacity. For each generation class it provides capacities and locations, their expected degree of *curtailment*, and DISCO incentives that maintain a specific financial state. Indeed the incentives reflect the ability to actively manage the network to extract latent capacity given growing RES quota requirements.

Chapter 7

Conclusions and Further Work

7.1 Thesis Summary

Network capacity allocation has been extensively studied in numerous forms. The main approach typically treats generation from different classes (SG and IPP) in the same manner and neglects combined aspects of on-site load and generation. Yet issues remain about the growing network presence of SG and its impact on network capacity and DISCO revenue, and effective regulation models and policies to coordinate SG and IPP integration. What sets the work of this thesis apart from existing research is that it: (1) unifies SG and IPP allocation and demonstrates its implications on shared host networks [208]; (2) utilises policy instruments constrained by limited financial resources, and (3) employs optimised revenue regulation that adapts to active network operation (such as [209]).

The problem can be studied from different perspectives. The DISCO and RA perspectives are sought in this thesis to appropriately characterise behaviour of each entity, and enable experimentation with realistic specifications within an optimisation framework. Chapter 3 characterises the allocation features of a standard OPF implementation. The implementation has several deficiencies when it comes to distributing capacity to SG and IPP. Hence, more explicit optimisation formulations, reflective of the DISCO's motives, are introduced to integrate both SG and IPP. The optimisation models provide an understanding of how far the DISCO can go to maximise its

profit, but the results will not be the most accurate in some cases because the role of SG in the quota mechanism is neglected and the incentives only change with SG and IPP capacity. Chapter 4 presents the SG and IPP capacity and location optimisation model with functions defining the full quota mechanism as well as revenue recovery and energy export incentives. For comparison, a different allocation approach is also presented. Specifically, it is demonstrated that planning with a typical objective such as capacity maximisation followed by heuristics for SG and IPP allocation would result in relatively poor allocative performance. That is, SG and IPP capacities and locations generate lower profits and constraint violations. Heuristics also have less potential to generalise and require customisation unique to every problem. Among the issues that arise in more general cases are: zero versus non-zero SG minimum requirement, budget constraints, low latent network capacity, adaptation to changing annual network demand, and IPP versus SG curtailment. In contrast, the proposed optimisation models better describe SG and IPP integration and the policy environment to which a profit-maximising DISCO is likely to be exposed. Indeed, case studies reveal that the DISCO can address the above-mentioned issues and still maximise profit.

The RA's viewpoint is interpreted in Chapter 5 as seeking to minimise the deviation of DISCO profit from the allowed profit as a function of variable revenue and conditional compliance costs. The RA does not know beforehand how much SG and IPP a specified budget can achieve. In addition, because of disparate characteristics among networks a defined quota can be met in one network but violated in another. To fulfil these needs the RA could institute flexible incentive determination. These determinations are tailored to the requirements of network operation, the DISCO, generators, and ratepayers. Regulation optimisation models are presented with these requirements in mind, providing the RA with a tool to know in advance whether its stated plans i.e., RES goals and budget, are achievable within existing sub-transmission and distribution networks. Therefore, the capability to solve the capacity and incentive allocation problem using our framework is attractive because it makes fewer data assumptions (e.g., network constraints) on the planning process. The RA may seek to evaluate the impact of increasing network utilisation and driving operation nearer to the network's physical

limits. The approach described in Chapter 6 supports this notion of advanced network operation by integrating ANM and suitably modifying incentives for the DISCO. By design, the formulation captures the relationship between network constraints and curtailment rather than relying on assumptions for predefined network capacity and curtailment.

All the models employ sets of daily profiles extracted from annual data. This constitutes a limitation of the results as they will be subject to the error of forecasted daily profiles. It is advisable to optimise representative daily profiles. As demonstrated in [131] the system cost error in some cases can be as low as 0.29% for optimised daily profiles but substantially higher for those selected with simpler heuristics. A low error points to the ability to preserve a relatively low computational cost while maintaining the accuracy of the results.

Another limitation is that even though curtailment is enabled, the resulting network capacity may be conservative relative to the higher dimensional case. This can be readily addressed within the model by increasing the allowed curtailment or increasing the dimensions of the time series, which will produce better estimates of curtailment. Nevertheless the extent of the above errors depends on the input data rather than the optimisation models in themselves. The models can be easily applied to extended series dimensions at the cost of computational speed.

A further assumption that can be easily addressed is the fixed price of electricity. In the same manner as dynamic generation and demand series, the price can be made variable. However, the model is not able to endogenously account for price changes that are caused by the new RES. Although the author recognises these and other limitations, the developed models represent an optimal baseline as other aspects are considered.

7.2 Implications and Significance

Use of the presented optimisation models necessitates the collection of network (e.g. layout, voltage and impedance) information, as well as demand and generation profiles, which must be part of standard reporting requirements.

A more static but simpler approach based on the proposed framework can be fol-

lowed. Indeed, the RA can develop a set of representative networks and feed them into the optimisation model to generate usable RES baselines. Suppose the representative networks are classified in terms of voltage levels (other characteristics such as urban/rural feeder markers can be included); a reference table can be drawn, with each voltage level and quota having a corresponding budget, SG, IPP, and incentives.

This approach would obviously require a larger number of calculations compared to when the RA knows exactly the network for which the DISCO issues RES connections. Nonetheless, the intensive computations are completed in advance, so a user would only need to refer to the generated tables during application. Of course these will guide the RA when assessing the DISCO's own RES estimates. Regardless of how the optimisation model is utilised, it offers the RA interpretable knowledge of RES integration in power networks.

The attractiveness of SG or behind-the-meter generation from existing DISCO customers depends on the exposure of the DISCO to incentives. These incentives can be newly created to promote new generation, or existing, within the prevailing regulatory framework. In particular, the thesis shows that, in constrained systems, the value of SG depends on the targets imposed on the connection of larger generation, particularly IPP. Allowing cost recovery for lost sales makes the DISCO agnostic to SG connections. But when coupled with cheaper energy exports, targets and other network benefits such as loss reduction, the marginal contribution of SG becomes positive.

Various scenarios arise, which are key to decision-making. Some are related to load changes. Load growth scenarios suggest that more demand—electric vehicle charging is one such example—will help avert revenue erosion. The extent to which this is effective is subject to the level of quota obligation. Regarding the required incentives for RES integration, the results suggest that large shares of capacity attributable to SG will inevitably lead to high incentives. This implies that the RA on behalf of consumers may have to determine maximum affordability level beyond which alternatives will have to be sought. One option is to eventually consider more sustainable business models such as allowing higher use-of-system charges for DG, and a return to be earned for network operation functions. Ultimately a phased SG integration approach that relies

on existing market structures can be implemented up to a specific SG cap, followed by changes to the SG programme or DISCO business models to enable further growth of SG.

Because of the use of optimisation-based formulations the work of this thesis has sufficient flexibility to handle additional data or extensions, which are presented in the next section.

7.3 Further Work

In the presented work, it is assumed that the support costs (e.g. SG-imposed revenue deficit) are borne by ratepayers. As the costs of RES development decline there is an increasing need to investigate the equitable balance and distribution of charges between generators and different types of consumers (those that have and those that do not have generators). To extend the work of the thesis in this way would require the consideration of further costs and benefits of renewable SG and IPP. Although many of them including the deferral benefit are well known, others such as the costs over more granular time-scales (e.g. the need for flexibility provision) draw interest.

Another promising theme for future study involves investigating incentives for increased utilisation of distribution energy resources to meet environmental and public policy goals. A good example is battery energy storage—it has the potential to change the characteristics of energy end-use and supply. However, the costs of battery storage can be a hindrance to consumer adoption. Typical energy tariffs for residential customers with PV systems are not sufficient enough to encourage customers with low PV self-sufficiency [210] to take up batteries. A strong signal to invest in batteries appears when there are low rates for excess generation and high tariffs for energy demand. Potential incentives will likely require spatial and temporal dimensions in order to send the correct signals to battery storage and other distributed energy resource owners.

Deterministic methods are applied in this thesis to problems that, in actuality, exhibit some degree of parameter uncertainty. Indeed, the decisions involving capacity allocation and incentive design are subject to error. For instance, the errors might lie in the forecast of demand and generation, as well as in model parameters. Furthermore,

the fact that the DISCO does not own SG and IPP creates the need to evaluate the risk to its operations. To better account for the imperfect data, uncertainty must be built into the optimisation model following a principled approach. Among the potential methods for obtaining robustness against uncertainty are stochastic optimisation and robust optimisation. The older of the two, stochastic optimisation, assumes the uncertainty can be characterised probabilistically. It enables decision-makers to assess the expected results in terms of their variability levels [211], for example, the trade-off between the DISCO's profit and its variability. Robust optimisation presents a deterministic and set-based approach to treating uncertainty. It is applicable even when parameter uncertainty is not stochastic or the underlying distribution is unknown. For a myriad of convex problems and some classes of uncertainty sets robust optimisation is tractable [212].

Although the proposed formulations avoid major simplifying approximations, questions remain about more computationally tractable formulations of the proposed non-convex nonlinear models. These alternative formulations would be able to better handle additional requirements such as the coordination of services between the distribution and transmission network operators, and the uncertain context mentioned above. A promising approach is to develop convex relaxations of the problem. However considerable care must be taken since their applicability is restricted. In other words, it will be necessary to find conditions in which the relaxations are sufficiently accurate and representative of the original problem.

Appendix A

Additional Data

Load and generation data for the 14-bus, 33-bus and 69-bus systems are shown here. The variable load and generation are drawn from the product of the scale factors of the load time series and bus demand, and the scale factors of the generation time series and calculated capacity at selected candidate buses.

Table A.1: Bus demand data for the 14-bus system

| Bus | P (MW) | Q (MVA _r) | Bus | P (MW) | Q (MVA _r) | Bus | P (MW) | Q (MVA _r) |
|-----|---------|-----------------------|-----|---------|-----------------------|-----|--------|-----------------------|
| 1 | 0 | 0 | 6 | 0.46725 | 0.23955 | 11 | 0 | 0 |
| 2 | 0.46725 | 0.23955 | 7 | 0.46725 | 0.23955 | 12 | 22 | 7.2310503 |
| 3 | 0.46725 | 0.23955 | 8 | 0.46725 | 0.23955 | 13 | 18 | 5.9163139 |
| 4 | 0.46725 | 0.23955 | 9 | 0.46725 | 0.23955 | 14 | 0 | 0 |
| 5 | 0.46725 | 0.23955 | 10 | 0.46725 | 0.23955 | | | |

Appendix A. Additional Data

Table A.2: Bus demand data for the 33-bus system

| Bus | P (MW) | Q (MVA _r) | Bus | P (MW) | Q (MVA _r) | Bus | P (MW) | Q (MVA _r) |
|-----|--------|-----------------------|-----|--------|-----------------------|-----|--------|-----------------------|
| 1 | 0 | 0 | 12 | 0.06 | 0.035 | 23 | 0.09 | 0.05 |
| 2 | 11 | 0.5 | 13 | 0.06 | 0.035 | 24 | 0.42 | 0.2 |
| 3 | 0.3 | 0.04 | 14 | 0.12 | 0.08 | 25 | 0.42 | 0.2 |
| 4 | 0.12 | 0.08 | 15 | 0.06 | 0.01 | 26 | 0.06 | 0.025 |
| 5 | 0.06 | 0.03 | 16 | 0.06 | 0.02 | 27 | 0.06 | 0.025 |
| 6 | 0.4 | 0.02 | 17 | 0.06 | 0.02 | 28 | 0.4 | 0.02 |
| 7 | 0.2 | 0.1 | 18 | 0.09 | 0.04 | 29 | 0.12 | 0.07 |
| 8 | 0.2 | 0.1 | 19 | 0.25 | 0.04 | 30 | 0.2 | 0.6 |
| 9 | 0.06 | 0.02 | 20 | 0.09 | 0.04 | 31 | 0.15 | 0.07 |
| 10 | 0.06 | 0.02 | 21 | 0.09 | 0.04 | 32 | 0.21 | 0.1 |
| 11 | 0.045 | 0.03 | 22 | 0.09 | 0.04 | 33 | 0.06 | 0.04 |

Appendix A. Additional Data

Table A.3: Bus demand data for the 69-bus system

| Bus | P (MW) | Q (MVA _r) | Bus | P (MW) | Q (MVA _r) | Bus | P (MW) | Q (MVA _r) |
|-----|--------|-----------------------|-----|---------|-----------------------|-----|---------|-----------------------|
| 1 | 0 | 0 | 24 | 0.028 | 0.02 | 47 | 0 | 0 |
| 2 | 0 | 0 | 25 | 0 | 0 | 48 | 0.079 | 0.0564 |
| 3 | 0 | 0 | 26 | 0.014 | 0.01 | 49 | 0.3847 | 0.2745 |
| 4 | 0 | 0 | 27 | 0.014 | 0.01 | 50 | 0.3847 | 0.2745 |
| 5 | 0 | 0 | 28 | 0.026 | 0.0186 | 51 | 0.0405 | 0.0283 |
| 6 | 0.0026 | 0.0022 | 29 | 0.026 | 0.0186 | 52 | 0.0036 | 0.0027 |
| 7 | 0.0404 | 0.03 | 30 | 0 | 0 | 53 | 0.00435 | 0.0035 |
| 8 | 0.075 | 0.054 | 31 | 0 | 0 | 54 | 0.0264 | 0.019 |
| 9 | 0.03 | 0.022 | 32 | 0 | 0 | 55 | 0.0244 | 0.0172 |
| 10 | 0.028 | 0.019 | 33 | 0.014 | 0.01 | 56 | 0 | 0 |
| 11 | 0.145 | 0.104 | 34 | 0.0195 | 0.014 | 57 | 0 | 0 |
| 12 | 0.145 | 0.104 | 35 | 0.006 | 0.004 | 58 | 0 | 0 |
| 13 | 0.008 | 0.005 | 36 | 0.026 | 0.01855 | 59 | 0.1 | 0.072 |
| 14 | 0.008 | 0.0055 | 37 | 0.026 | 0.01855 | 60 | 0 | 0 |
| 15 | 0 | 0 | 38 | 0 | 0 | 61 | 1.244 | 0.888 |
| 16 | 0.0455 | 0.03 | 39 | 0.024 | 0.017 | 62 | 0.032 | 0.023 |
| 17 | 0.06 | 0.035 | 40 | 0.024 | 0.017 | 63 | 0 | 0 |
| 18 | 0.06 | 0.035 | 41 | 0.0012 | 0.001 | 64 | 0.227 | 0.162 |
| 19 | 0 | 0 | 42 | 0 | 0 | 65 | 0.059 | 0.042 |
| 20 | 0.001 | 0.0006 | 43 | 0.006 | 0.0043 | 66 | 0.018 | 0.013 |
| 21 | 0.114 | 0.081 | 44 | 0 | 0 | 67 | 0.018 | 0.013 |
| 22 | 0.005 | 0.0035 | 45 | 0.03922 | 0.0263 | 68 | 0.028 | 0.02 |
| 23 | 0 | 0 | 46 | 0.03922 | 0.0263 | 69 | 0.028 | 0.02 |

Appendix A. Additional Data

Table A.4: Daily generation and load profiles using scale factors

| Hour | Generation | | Load | | | |
|------|------------|--------|--------|--------|--------|--------|
| | P_a | P_b | P_a | Q_a | P_b | Q_b |
| 1 | 0.29 | 0.1333 | 0.4259 | 0.302 | 0.3228 | 0.2289 |
| 2 | 0.32 | 0 | 0.4143 | 0.3082 | 0.314 | 0.2336 |
| 3 | 0.3 | 0 | 0.4136 | 0.3042 | 0.3135 | 0.2305 |
| 4 | 0.24 | 0 | 0.4294 | 0.2983 | 0.3254 | 0.2261 |
| 5 | 0.21 | 0 | 0.4775 | 0.2772 | 0.3619 | 0.2101 |
| 6 | 0.16 | 0 | 0.5865 | 0.2793 | 0.4445 | 0.2117 |
| 7 | 0.14 | 0 | 0.889 | 0.3114 | 0.6124 | 0.226 |
| 8 | 0.15 | 0 | 1.1784 | 0.3306 | 0.6237 | 0.236 |
| 9 | 0.17 | 0.0667 | 1.1224 | 0.3516 | 0.6106 | 0.2465 |
| 10 | 0.27 | 0.2667 | 0.6773 | 0.3468 | 0.5133 | 0.2628 |
| 11 | 0.22 | 0.0667 | 0.6381 | 0.3434 | 0.4836 | 0.2603 |
| 12 | 0.19 | 0.1333 | 0.6266 | 0.3548 | 0.4749 | 0.2689 |
| 13 | 0.24 | 0.2 | 0.5905 | 0.3463 | 0.4475 | 0.2624 |
| 14 | 0.26 | 0.1333 | 0.5661 | 0.3549 | 0.429 | 0.269 |
| 15 | 0.32 | 0.2 | 0.5428 | 0.3499 | 0.4114 | 0.2652 |
| 16 | 0.31 | 0.3333 | 0.5521 | 0.3305 | 0.4184 | 0.2505 |
| 17 | 0.28 | 0.8 | 0.6657 | 0.318 | 0.5045 | 0.241 |
| 18 | 0.33 | 1 | 1.2696 | 0.3334 | 0.8622 | 0.2527 |
| 19 | 0.35 | 1 | 1.2733 | 0.3461 | 0.865 | 0.2623 |
| 20 | 0.38 | 1 | 1.0175 | 0.3416 | 0.7711 | 0.2589 |
| 21 | 0.4 | 1 | 0.6926 | 0.316 | 0.5249 | 0.2395 |
| 22 | 0.36 | 1 | 0.5642 | 0.2905 | 0.4276 | 0.2202 |
| 23 | 0.33 | 1 | 0.4613 | 0.2804 | 0.3496 | 0.2125 |
| 24 | 0.3 | 1 | 0.4109 | 0.2807 | 0.3164 | 0.2127 |

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