Exploring future opportunities and challenges of Demand Side Management with Agent Based Modelling

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I, Dina Subkhankulova, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

Abstract

Electricity systems worldwide are transforming in-line with the global decarbonisation goals. On the supply side, renewable energy resources are replacing fossil fuels which introduces uncertainty in electricity generation. On the demand side, heating and transport electrification coupled with continuous integration of small scale renewables and energy storage are transforming the interactions between consumers and generators. These changes are raising new challenges for system operators in terms of balancing electricity in the grid.

Demand-side management (DSM), whereby electricity consumption is coordinated with variable supply from renewables, has been shown to offer a promising solution to the above problem. However, the extent to which the future impact of DSM has been holistically assessed is arguable. Current model-based assessment of DSM primarily focuses on its benefits, ignoring the potential challenges since the testing tends to be carried out in an isolated and idealistic setting.

This work proposes a model for Electricity System Management using an Agent based approach (or ESMA), which includes heterogeneous consumers, aggregators, the system operator, and market. The main feature of the model is its capability to simulate different regimes of DSM: decentralised (performed by consumers), semi-centralised (performed by aggregators), and centralised (performed by the system operator). The impact of each DSM regime is assessed in terms system costs, greenhouse gas emissions and consumer bills in the context of the British electricity system for 2015-2050.

It is found that a trade-off exists between consumer autonomy and system optimality with regards to DSM. It is argued that the level of information sharing between consumers and the system can be minimised, as better learning and predicting algorithms are developed. The thesis is concluded with a discussion on the potential consumer tariff structure which would reward consumer flexibility.

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Impact Statement

This research investigates the future impact of deploying demand side management (DSM) in a decentralised electricity system. In order to do that, a bespoke Electricity System Management Agent based model (ESMA) has been built, whereby electricity can be managed by one of three stakeholder types: consumers, aggregators, and the system operator. The investigation is carried out in the case of the British electricity system in two boundary scenarios: Steady State and Two Degrees+.

Firstly, the impact of this research is regulatory. It highlights the need for better regulation of activity between electricity utilities and end-users, as well as requirements for more flexible and tailor-made end-user electricity tariffs. This research explicitly demonstrates how incentivising end-users to consumer electricity more efficiently with a real time price can lead to system losses as the market herds towards the same cheap electricity time periods. The work also explores the negative consequences of energy utilities using DSM in order to compete in the market and how allowing consumers to switch aggregators can aggravate the situation. Although the analysis has been carried out in the case of the British electricity system, the findings are applicable to any electricity market undergoing decentralisation and so extend internationally. The results are primarily aimed at the energy regulator and system operator but are also relevant to electric utilities and end-users.

Secondly, the impact is methodological. A bespoke open-source agent-based model has been developed capable of simulating the interactions of an electricity market undergoing decentralisation. The model considers different regimes for demand side management ranging from a decentralised (performed by consumer), semi centralised (performed by the aggregator), and centralised (performed by the system operator). ESMA incorporates four economic demand sectors, with explicit modelling of heat and transport electrification. Finally, a new method for decentralised DSM has been developed, which enables consumers to optimise day-ahead electricity consumption by learning from past behaviour. As a result, feeding real time prices becomes an effective way of coordinating consumers without raising end-user privacy concerns.

The ultimately impact of this research is a more sustainable consumption of electricity. The long-term benefits include decreased greenhouse gas emissions and lower electricity prices, and as a result improved quality of the environment and quality of life.

List of publications

1. D. Subkhankulova, M. Barrett, A. Baklanov, D. McCollum, and E. Manley. Balancing variable supply with flexible demand. In *European Council for Energy Efficient Economy (ECEEE) Summer Study 2017.*, 2017c

2. D. Subkhankulova, A. Baklanov, and D. McCollum. Demand Side Management: A Case for Disruptive Behaviour. In *Advanced Computational Methods for Knowledge Engineering. Proceedings of the 5th International Conference on Computer Science, Applied Mathematics and Applications, ICCSAMA 2017.*, pages 47–59. Springer, 2017b. doi: 10.1007/978-3-319-61911-8_5

3. D. Subkhankulova, A. Baklanov, and D. McCollum. Demand Side Management: A case for disruptive behaviour. In *Fifth Green Growth Knowledge Platform Annual Conference (GGKP 2017)*, 2017a

4. G. Castagneto Gissey, D. Subkhankulova, P. E. Dodds, and M. Barrett. Value of energy storage aggregation to the electricity system. *submitted to Energy Policy*, 2018

List of abbreviations

A/C Air conditioning

ABM Agent based modelling

AGG Aggregator

AGG_CM Demand side management algorithm coordinated by an aggregator for the purpose of cost minimisation

AGG_DF Demand side management algorithm coordinated by an aggregator for the purpose of demand flattening

AGG_DSM Demand side management algorithm coordinated by an aggregator

AS Ancillary Services

BEIS Department for Business, Energy & Industrial Strategy

BMU Balancing mechanism unit

CAP Capacity market

CCGT Combined cycle gas turbine

CCS Carbon capture and storage

CHM Cambridge housing model

CHP Combined heat and power

CON Consumer

CON_CM Demand side management algorithm coordinated by a consumer for the purpose of minimising cost

CON_DSM Demand side management algorithm coordinated by a consumer

COP Coefficient of performance

CPP Critical peak pricing

DER Distributed energy resource

DLC Direct load control

DR Demand response

DSM Demand side management

EEU Expected Energy Unserved

EH Electric heating

ES Electrical store

ESMA Electricity System Management Agent based model

EV Electric vehicle

FES Future energy scenarios

FFR Firm frequency response

GB Great Britain

GHG Greenhouse gas

HP Heat pump

I/C Interruptible/Curtailable services

IPCC Intergovernmental panel on climate change

LOLE Loss-of-load expectation

LP Linear programming

MAS Multi-agent system

mCHP micro-CHP

MILP Mixed integer linear programming

NLP Non-linear programming

OCGT Open cycle gas turbine

OTC Over the counter

PEV Plug-in electric vehicle

PS Pumped storage

PV Photovoltaic

RH Resistance heating

RTP Real time price

SO System Operator

SO_CM Demand side management algorithm coordinated by the system operator for the purpose of minimising cost

STOR Short term operating reserve

TES Thermal energy store

UK United Kingdom

UNFCC United Nations Framework Convention on Climate Change

VPP Virtual power plant

List of definitions

Aggregator - an entity which is able to pool consumers together. An aggregator can represent an energy utility (in which case it retails wholesale electricity to end-users), or a Balancing Service Provider in which case it instructs end-users on how to shift demand.

Ancillary services - services and functions used by the system operator in order to balance supply and demand in the grid (also referred to as Balancing services). Examples include frequency response, reserve services, reactive power services (Energy UK, 2017).

Balancing mechanism - a tool used by the National Grid for the purpose of removing imbalances between system demand and supply. Balancing mechanism gets activated at gate closure (or 1 hour before physical delivery of power) and runs like a market where the system operator procures services from the balancing mechanism units (BMUs).

Baseload - the minimum level of electricity demand required by the system over a period of 24 hours. It is needed to provide power to components that keep running at all times (also referred as continuous load). Base load is typically met by invariable generators like nuclear and coal[1].

Black start - refers to the procedure when power in the grid is restored in the event of a total or partial shutdown of the national electricity transmission system[2].

[1] http://sinovoltaics.com/learning-center/basics/base-load-peak-load/

[2] https://www.nationalgrid.com/uk/electricity/balancing-services/system-security-services/black-start

Copper plate - an approximation made when modelling the electricity system, which assumes that power can flow unconstrained from any generation site to any demand site therefore ignoring physical constraints of the grid.

Dispatchable generation - electricity sources which can generate electricity on demand, e.g. coal or gas power plants.

Distributed energy resources (DERs) - electricity generating resources or flexible loads that are directly connected to a local distribution system or a host facility within the local distribution system. These include solar panels, electricity storage, electric vehicles, heat pumps, small scale combined heat and power generators (Ieso, 2018).

Dynamic pricing - type of time variable pricing, whereby electricity price changes throughout the day to reflect the real time cost of electricity generation. Examples of dynamic pricing include real time pricing (RTP), time-of-use (TOU) and critical peak (CPP)[3].

Electricity tariff - retail price of electricity.

Energy utility - company which supplies consumers with energy.

Flexible load - part of consumer demand which can be shifted in time, e.g. from an electric vehicle, battery or air conditioning.

Gate closure - the cut-off time of wholesale electricity trading (1 hour before physical delivery), also referring to the start of the balancing market.

Hot standby - refers to the situation when a generation unit is held in the state of readiness[4].

Load factor - ratio between average to peak demand.

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[3] https://cdn.eurelectric.org/media/2113/dynamic_pricing_in_electricity_supply-2017-2520-0003-01-e-h-7FE49D01.pdf

[4] https://www.nationalgrid.com/uk/electricity/balancing-services/reserve-services/bm-start.

Merit order stack - whereby generation units are arranged in the ascending order of price for electricity (which often reflects the short run marginal cost of production).

Microgrid - collection of electricity generation resources and loads that can operates connected to and synchronous with the national electricity grid, or disconnect to ‘island mode’ and function autonomously.

National Grid - system operator of the British electricity grid.

Non-deferrable demand - corresponds to activities requiring energy which cannot be shifted in time, e.g. watching TV, lighting (in the case of electrical energy) and heating (in the case of thermal energy).

Non-thermal demand - weather independent energy demand, e.g. lighting, operation of machinery.

Over the counter trade - electricity deal whereby the terms are agreed in private.

Renewable generation - electricity sources which generate electricity from renewable energy, e.g. solar, wind, and hydro.

Smart meter - a device which is able to measure electricity consumption and the cost of its generation in real time.

System frequency - a measure of the balance between electricity supply and demand in the grid.

Thermal demand - weather dependent energy demand required for heating and cooling, e.g. water and space heating.

Time variable pricing - whereby the price for electricity varies throughout the day depending on the cost of generating electricity, e.g. time-of-use (TOU) pricing.

List of symbols

α Damping term which supresses consumer response to real time prices

α^c Consumer specific damping term which supresses consumer response to real time prices

δ^j_{ramp} Absolute change in power generation from time $t-1$ to t of technology j [MW]

$\varepsilon(t,d)$ Wholesale price uplift reflecting network and balancing costs [£/MWh]

η^j Efficiency of generation technology j

η_{boiler} Efficiency of boiler

η^c_{ES} Efficiency of electrical storage of consumer c

η^c_{HP} Efficiency of a heat pump of consumer c in converting electricity to heat

η^{max}_{HP} Carnot (or the theoretical maximum) efficiency of the heat pump of consumer c

η^c_{RH} Efficiency of a resistance heater of consumer c in converting electricity to heat

η^c_{TES} Efficiency of an electrical store of consumer c

$\mathscr{A}$ Set of all aggregators

$\mathscr{C}$ Set of all consumers

$\mathscr{C}^a$ Set of all consumers supplied by aggregator a

$\mathscr{G}$ Set of generation technologies at the transmission level

$\mathscr{S} = \{dom, com, ind, trans\}$ Set of consumer sectors (domestic, commercial, industrial and transportation)

$\mathscr{T} = \{HP, PV, ES, TES\}$ Set of consumer technologies

$\pi^a(t,d)$ Retail price offered by aggregator a in time t of day d [£/MWh]

θ_{ext} External air temperature [°C]

θ_{TES} Temperature of water in a thermal energy store [°C]

a Aggregator identifier index

$aggDR \in [0,1]$ Share of aggregators participating in DSM

b_{ES}, b_{TES} Binary variable (0,1) which determines whether the energy storage is charging or discharging

c Consumer identifier index

$C^a(d)$ Cost of power incurred by aggregator a in day d [£]

$C^a(y)$ Cost of power incurred by aggregator a in year y [£]

C^j_{dyn} Dynamic cost of generation of technology j [£]

c^j_{fu} Fuel cost required by generation technology j [£/MWh]

c^j_{op} Variable operational and maintenance cost of generation technology j [£/MWh]

C^j_{SRUC} Short run unavoidable cost of generation of technology j [£]

c^j_{MC} Marginal cost of generation by technology j [£/MWh]

c^j_{ramp} Ramping cost of generation technology j per unit of change in demand [£/MWh]

cap^j Capacity of generation technology j [MW]

$conDR \in [0,1]$ Share of consumers participating in DSM

$conExplore$ Proportion of the time consumer c explores the new strategy when learning α^c

$conStep$ The deviation taken by consumer c from the α^c during the α learning algorithm

$E^{EV,max}, E^{EV,min}$ Maximum and minimum energy storage capacity of electric transport consumer [MWh]

$E_{PS}^{min}, E_{PS}^{max}$ Minimum and maximum energy constraints of pumped storage [MWh]

$E_{ES}^{max,c}, E_{ES}^{min,c}$ Maximum and minimum energy capacity constraints of electrical storage of consumer c [MWh]

$E_{TES}^{max,c}, E_{TES}^{min,c}$ Maximum and minimum energy capacity constraints of thermal energy storage of consumer c [MWh]

$f(t,d,m)$ Traffic flow distribution

G Total number of generating technologies

$g^k(t)$ Coordination signal sent by the aggregator to consumers at time t in iteration k

h_{CO2}^j Emissions factor of generation technology j [tonne CO2eq/MWh]

j Generation technology index

k Iteration counter used in the DSM scheduling algorithm

$L(t,d)$ Electricity system demand outturn at time t in day d [MWh]

$L^a(t,d)$ Total electricity demand of aggregator a at time t in day d [MWh]

$l^c(t,d)$ Non-deferrable electricity demand of consumer c at time t in day d [MWh]

$l^c_{exp}(t,d)$ Electricity exported by consumer c at time t in day d [MWh]

$l^c_{net}(t,d)$ Net or residual electricity demand of consumer c at time t in day d [MWh]

$L^{ch}_{PS}(t,d), L^{dc}_{PS}(t,d)$ Charge and discharge profiles of transmission level pumped storage at time t in day d [MWh]

$l^{EV,ch}(t,d), l^{EV,dc}(t,d)$ Charge and discharge profiles of an electric transport consumer at time t in day d [MWh]

$l^{EV,max}, l^{EV,min}$ Maximum and minimum power storage capacity of electric transport consumer [MW]

$l^{fleet,ch}(t,d), l^{fleet,dc}(t,d)$ Charging and discharging profiles of an electric vehicle fleet in time t of day d

$L^{min}_{PS}, L^{max}_{PS}$ Minimum and maximum power constraints of pumped storage [MW]

$l^{sec}_{tot}, l^{sec}, l^{sec}_{therm}$ Total, non-thermal and thermal electricity demand profile by a real life end-user from economic sector $sec \in \mathscr{S}$ at time t in day d [MWh]

$L_{agg}(t,d)$ Electricity demand summed across all aggregators at time t in day d [MWh]

$l^{ch,c}_{ES}(t,d), l^{dc,c}_{ES}(t,d)$ Electrical storage charge and discharge profiles of consumer c at time t in day d [MWh]

$l^{max,c}_{ES}, l^{min,c}_{ES}$ Maximum and minimum power capacity constraints of electrical storage of consumer c [MW]

$L_{gen}(t,d)$ Power output from all generation technologies in time t of day d [MW]

$l^c_{HP}(t,d)$ Electricity demand profile by a heat pump of consumer c at time t in day d [MWh]

$l_{HP}^{max,c}, l_{HP}^{min,c}$ Maximum and minimum power constraints of a heat pump of consumers c [MW]

$L_{import}(t,d)$ Imported electricity at the transmission level at time t in day d [MWh]

$L_{loss}(t,d)$ Losses experienced by the electricity system at time t in day d [MWh]

$l_{RH}^{c}(t,d)$ Electricity demand profile by a resistance heater of consumer c at time t in day d [MWh]

$l_{RH}^{max,c}, l_{RH}^{min,c}$ Maximum and minimum power constraints of a resistance heater of consumers c [MW]

M Total number of aggregators

m_{type}^{sec} Consumer multiplier which corresponds to the actual number of end-users each agent of sector sec and type $type$ represents

N Number of consumers

$N_{stat}^{EV}(t,d), N_{move}^{EV}(t,d), N_{tot}^{EV}(t,d)$ Number of stationary, moving and total electric vehicles in time t of day d

n_{type}^{sec} Number of consumer agents of specific sector and type

$p(t,d)$ Wholesale electricity price [£/MWh]

$p_{CO2}(y)$ Carbon price in year y [£/tonne CO2eq]

$p_{SR}(t,d)$ Short run wholesale electricity price excluding uplift $\varepsilon(t,d)$ [£/MWh]

$q^{c}(t,d)$ Non-deferrable heat demand of consumer c at time t in day d [MWh]

q^{j} Power generated by technology j [£/MWh]

$q_{CHM,heat}^{dom}(t,d), q_{CHM,gas}^{dom}(t,d)$ Heat and gas consumption by a domestic end-user according to the Cambridge Housing Model in time t of day d [MWh]

$q^c_{HP}(t,d)$ Heat output from a heat pump of consumer c at time t in day d [MWh]

$q^c_{RH}(t,d)$ Heat output from a resistance heater of consumer c at time t in day d [MWh]

$q^{ch,c}_{TES}(t,d), q^{dc,c}_{TES}(t,d)$ Thermal energy storage charge and discharge profiles of consumer c at time t in day d [MWh]

$q^{max,c}_{TES}, q^{min,c}_{TES}$ Maximum and minimum power capacity constraints of thermal energy storage of consumer c [MW]

$R(t,d)$ Transmission level renewable generation at time t in day d

$r^c(t,d)$ Renewable generation profile of consume c at time t in day d [MWh]

$R_{used}(t,d), R_{curt}(t,d)$ Used and curtailed renewable generation at time t in day d

T,D,Y Maximum number of hours in a day, days in a year and years of simulation

t,d,y Hour, day and year indices

$type_i$ Consumer type which represents the type of resources the consumer has access to, where $i \in [1,10]$

w Weighing parameter between 0 and 1 for previous system demand outturn

$z^c(d)$ Cost incurred by consumer c in day d

* Indicates a predicted value

Chapter 1

Introduction

1.1 The balancing challenge

Climate change is recognised as one of the biggest challenges of the 21st century. Following the 21st Conference of the Parties of the United Nations Framework Convention on Climate Change (UNFCCC) held in Paris, 195 states pledged to reduce their greenhouse gas (GHG) emissions in order to avoid irreversible effects of global warming (UNFCCC, 2016). Electricity and heat production contribute a quarter of the total GHG emissions globally (IPCC, 2014), for which reason countries worldwide are working on making their electricity systems more sustainable.

On the supply side, fossil fuel power plants (such as coal and gas) are being replaced by renewable generators like biomass, onshore and offshore wind, and solar. However, much of the renewable energy supply is variable and uncontrollable meaning that electricity cannot be generated on demand like in the case of dispatchable power plants.

On the demand side, the need to decarbonise is driving the electrification of transportation and heat, the integration of renewable (e.g. solar and wind) and more energy efficient (e.g. combined heat and power, CHP) generation technology and storage. As a result, the demand side is witnessing the integration of a multitude of distributed energy resources (or DERs), such as electric vehicles, heat pumps, batteries, rooftop solar, micro-CHP and small scale wind generators. Coupled with the increasing accessibility of energy management and communication devices (such as smart meters and home control systems), DERs are changing the way electricity is consumed making the demand side more proactive and unpredictable. Balancing variable electricity supply with increasingly more unpredictable demand is presenting a major challenge for power system operators all over the world.

Demand-side management (DSM) refers to the modification of consumer demand for electricity in order to optimise the dispatch of available generation resources, and minimise the cost of maintaining a balanced flow of power in the grid.

DSM has been attracting a lot of attention from academia and industry as a promising solution to the *balancing challenge*, by means of altering demand to better accommodate for variable renewable supply (Ofgem, 2017a). Yet, as electricity systems are transforming, the full scope of DSM impact has not yet been understood.

1.2 The decentralisation of electricity system management

The concept of electricity system management is not new. Since the creation of power networks, electricity supply and demand had to be balanced in the grid in real time, as it is notoriously expensive to store. Traditionally, the system operator (SO) was responsible for ensuring a smooth flow of electricity in the grid, due to its centralised design and the computational requirements for processing large amounts of information.

Electricity balancing services on the supply side are typically provided by large power plants which can be ramped up and down in order to increase and decrease generation. In the UK, a condition for power generators to be connected to the transmission network is to have the ability to perform 'mandatory frequency response' - a service which involves balancing the grid within seconds of an event occurring (National Grid, 2017b).

Schemes to manage electricity consumption have been traditionally aimed at influencing human behaviour through time variable pricing. In the UK off-peak electric heating was introduced as early as 1960s with the intention to shift residential consumer demand to times of low electricity prices at night (Carlsson-Hyslop et al., 2013). 'The Triad' scheme, whereby utilities are penalised for consuming electricity during the three most expensive half-hours during the year, is an example of a DSM program aimed at non-domestic consumers (National Grid, 2015a).

Lowering costs for electricity storage, small scale generators and access to data communication and processing technology have reignited political, industrial and academic interest in demand side management. DSM schemes have been rapidly emerging all over the world in the last few decades, especially in warmer regions where synchronous operation of air conditioning can lead to the creation of large demand peaks. For example in the United States, Southern California Edison offers a discounted summer tariff in exchange for having consumer permission to switch off air conditioning for a short period of time (SCE, 2017). Other examples include a scheme run by OhmConnect, whereby the utility sends end-users a message to reduce consumption sometime in the near future in exchange for a financial payment (OhmConnect, 2017). In the UK, aggregators like KiWi Power contract non-domestic consumers to have the ability of controlling certain devices like fridges and freezers in exchange for a financial incentive (KiWi Power, 2018). In order to encourage the residential sector to consume electricity more sustainably, the UK government plans to integrate each household with a smart meter by 2020, which would inform end-users of the true cost of generating electricity in real time (Smart Energy GB, 2016).

The utility business models are also changing in recognition of the benefits of DSM. Tempus Energy is an energy utility which uses machine learning in order to instruct end-users when to consume electricity. By doing so, Tempus aims to reduce the projected cost of power purchased from the wholesale market and offer a more competitive retail tariff to consumers (Tempus, 2018). In more recent years, the emergence of blockchain technology has been an important driver for the 'peer-to-peer' electricity trading model, whereby smaller consumers are able to buy and sell electricity through an online platform without having to access the wholesale market. Brooklyn microgrid (a pilot implemented by LO3 and Siemens), is one example of how this model can work in the real world (LO3 Energy, 2018)[1].

In order to facilitate the decentralisation of the electricity system, the responsibility for maintaining a balanced grid must shift away from the System Operator towards distribution network operators (DNOs). This is especially relevant when considering embedded renewable generation which is not registered at the transmission level. For this reason the National Grid has been working on improving the cooperation with DNOs, which are required to take a more active role is managing generation and demand resources in the grid (National Grid, 2017c). Some responsibilities envisioned for future distribution system operators (DSOs) include (Butcher, 2017):

1. actively facilitating local electricity market for DERs in order to balance the distribution grid,
2. owning and/or operating electric vehicle charging infrastructure,
3. providing energy efficiency and environmental consultancy services,
4. owning and/or operator of power storage and CHP plant in order to meet demand in case of system scarcity.

Initiatives undertaken by DNOs today include offering DSR services to the grid, such as in the case of the Northern Powergrid. Facilitated by a contract with an aggregator Kiwi Power, the DNO operates a 2.5MW battery in order to provide frequency response services to the high-voltage transmission network. In fact, the electricity market regulator Ofgem claims that across all DNOs electrical storage adds up to around 12.6MW. The concern with regards to DNOs owning storage is that it could interfere with the development of a competitive market for flexibility services [2]. For this reason Ofgem introduced regulations, which allow DNOs to own but not operate storage. To conclude, DNOs will play an increasingly more active role in managing the electricity grid in the future, but the way this transition happens is critical to the competiveness and efficiency of the future smart grid.

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[1] See `https://www.brooklyn.energy/` for more information

[2] See https://www.energy-storage.news/news/uk-regulator-sets-rules-on-dno-ownership-of-energy-storage-as-one-puts-us5m

1.3 Motivation for research

As different types of stakeholders, such as consumers and aggregators, gain the technological capacity to manage electricity demand and supply at the local level, electricity system management on the whole is becoming more decentralised. Although these changes introduce many benefits and opportunities in making the electricity grid more sustainable (for example better utilisation of local renewable generation and storage), these do not come without a set of challenges. This is because a decentralised electricity system constitutes an interconnected and complex network of agents, central to which is the electricity market where prices are set depending on the aggregate system demand. Consequently, actions taken by a single agent can affect the whole market.

One of the main concerns with regards to the future implementation of DSM is *consumer herding* – a situation when end-users shift demand to the same periods of low electricity prices for the purpose of reducing the cost of electricity. When a large enough number of consumers adopt the same strategy, it can result in increased demand peaks, costs, and GHG emissions. Some studies already report that consumer response to the same price signals can lead to the creation of new demand peaks (Gottwalt et al., 2011; Ericson, 2009). Thinking further into the future when consumer flexibility is projected to be much higher and consumer tariffs more dynamic, herding is likely to become much more of an issue.

Aggregators can help alleviate the problem of consumer herding through coordinated DSM, but only up to a point where they become greedy and start to exploit their ability to shift demand in order to compete in the wholesale market. The first point of concern is *aggregator herding*, the negative consequences of which are exactly the same as consumer herding since aggregators merely instruct consumers to shift demand. Another point of concern is *strategic manipulation of flexible demand* by vertically integrated utilities, which has been shown to increase wholesale electricity prices (Prüggler et al., 2011). Since a vertically integrated utility profits from selling electricity at high prices, it would be in the utility's interest to strategically increase system demand and therefore prices.

Involving a central coordinator such as the System Operator can provide a way of avoiding consumer and aggregator herding. However, this would involve consumers sharing information on their consumption or flexibility (something that might not seem appealing to some due to *privacy concerns*). An alternative to this is decentralised coordination, whereby decisions are made locally rather than by a central entity. However, the extent to which decentralised coordination has been tested in the context of the whole system is limited.

Another major challenge of future DSM implementation is *cost allocation* to different types of consumers. Whereas end-users with flexible resources (such as electrical storage) act as price makers, inflexible consumers (which cannot alter their demand) are price takers. Yet, the prices for electricity are set in the wholesale market depending on the demand by the whole system. And so, it is important to reward consumers for being flexible without penalising those who do not have the resources to adjust demand. Appropriately structured electricity tariffs can address this problem. Dynamic pricing has been shown to incentivise end-users to consume electricity more efficiently, yet it can lead to chaotic system demand and electricity prices. In contrast, flat tariffs do not account for time variability of consumer demand and so do not incentivise load shifting. Hence the main challenge in structuring the future electricity tariffs lies in *encouraging flexibility and proactiveness, whilst ensuring system security*.

To summarise the above points, there are two major challenges with regards to the future deployment of demand side management:

1. *Control*, or rather to whom and to what extent it can be given. Centralised coordination can ensure that the grid is scheduled in an optimal manner, however stakeholders beyond the central coordinator lose (or partially lose) their autonomy. In contrast, if multiple stakeholders are permitted to act freely, it can harm the system as the market becomes chaotic.

2. *Cost allocation* once DSM has been implemented. Inappropriate electricity tariff structure can discourage consumer participation in DSM and adoption of DERs, whereas effective pricing of electricity can act as a strong driver for

building a sustainable energy system.

Demand side management can prove to be an effective tool in ensuring a balance in the future electricity grid where renewable energy capacity and consumer flexibility are high. However, this would not be possible without addressing the above challenges, which is the main motivation for this research.

1.4 Research contributions and scope

In view with the revived interest in demand side management, a lot of focus by the research community has been given to assessing the impact of DSM on the electricity system (Boßmann and Eser, 2016; Yang et al., 2014). However, the extent to which existing literature addresses the future challenges of DSM is arguable.

A large number of studies focus on the control aspect of implementing DSM, yet they tend to test it in a stylised setting, e.g. where a set of homogeneous consumers are being coordinated by a single aggregator (Voice et al., 2011; Gan et al., 2013), by aggregating consumer agents to a single load curve (Chen et al., 1995), or representing generation by a historical price function (Vytelingum et al., 2010). On the other side of the spectrum are whole system models like (Strbac et al., 2012; Fehrenbach et al., 2014), which pay a lot of attention to incorporating detailed information on demand and generation but assume perfect consumer and market behaviour in order to perform global optimisation. Consequently, dynamic interactions between autonomous stakeholders are lost and issues of consumer herding and aggregator competition are left unexplored. Others focus on the benefits of specific technologies like electric vehicles (EVs) or heat pumps (HPs) but perform analysis only for a single year (Lund and Kempton, 2008) or even a single day (Papadaskalopoulos et al., 2013). The question of cost allocation to different type of consumers is rarely explored. Moreover, simulations tend to be carried out with historical data thus limiting the findings to past years. Finally, studies on DSM do not consider all consumer sectors (often focusing on residential consumers only (Ramchurn et al., 2011)), which ignores the issue of demand-side interconnectedness.

The electricity system constitutes a complex and interconnected network of agents, which are coupled via the wholesale market. In order to holistically assess the impact of DSM, it is necessary to consider it in the context of the whole system. Taking observations outside of the wider system context can lead to the omission of vital system dynamics and the overlooking of potential challenges of DSM.

Up until now, the impact of DSM has not been addressed holistically meaning that analysis has either been carried out on part of a system, or by ignoring certain stakeholder interactions. The objective of this work is to explore the long-term impact of DSM in the context of a decentralised electricity system, where different stakeholders have their own agenda for deploying DSM.

This PhD explores not only the benefits but also the challenges of future deployment of demand side management paying particular attention to extreme stakeholder behaviour, such as competition for cheap power.

1.4.1 Research questions

The objective of this work is to answer the following research questions:

1. Up to which point is autonomous consumer cost minimisation based on the real time price effective in reducing system costs and greenhouse gas emissions?

2. How can aggregators facilitate effective demand side management and what potential risks might they bring along?

3. What is the appropriate tariff structure for rewarding consumer flexibility?

4. Is it possible for consumers to schedule demand autonomously without compromising the stability and sustainability of the electricity system?

In order to address the above research questions a bespoke model for Electricity System Management using an Agent based approach (or ESMA) is proposed. The model integrates four economic sectors (domestic, commercial, industrial and transport) represented by autonomous, competing consumers with varying flexible resources (e.g. heat pumps, resistance heating, thermal storage, electrical storage, and solar PV) and electricity demand profiles. Supplying consumers with power is the market composed of dispatchable and renewable energy resources which are scheduled based on the short-run marginal cost of electricity generation. The retail market consists of aggregators capable of coordinating consumers to shift electricity demand. In turn, consumers are able to switch aggregators based on the daily tariffs offered to them.

ESMA is built using a bottom-up approach allowing it to perform analysis into the future. The main feature of the model is that it allows demand scheduling at three hierarchal levels: consumer, aggregator and the system operator. ESMA is applied in order to analyse the impact of DSM in the context of the British electricity grid for the period of 2015-2050. In particular, it is used to investigate the consequences of consumer herding and aggregator competition, the value of a well-coordinated DSM, and the issue of cost allocation to different types of consumer.

1.4.2 Research contributions

To summarise, the contributions of this PhD are as follows:

1. A *holistic energy systems model* is developed, which includes heterogeneous consumers (representing four economic sectors), aggregators and the system operator. The model explicitly considers electricity generation (including renewables and pumped storage), as well as different regimes of hierarchal demand side management ranging from totally decentralised to totally centralised.

2. The issues of *control* and *stakeholder autonomy* are investigated by comparing the benefits to the system and consumers under each demand side management regime. Situations are identified where a conflict of interest exists between consumers, aggregators and the system in terms of financial benefits to each side as a result of DSM deployment.

3. This work investigated the issue of *cost allocation* to different types of end-users (i.e. with different resources and demand profiles) by comparing their savings as a result of DSM deployment under dynamic and flat tariffs.

4. An *autonomous decentralised DSM algorithm* is developed, whereby consumers are able to learn the right response strategy to real time electricity prices based on the outcome from the previous days.

5. The analysis is performed considering two extreme scenarios for the evolution of the British electricity grid for the period of 2015-2050. These consist of the Steady State scenario (where renewable capacity and consumer flexibility are low) and Two Degrees+ (where renewable capacity and consumer flexibility are high).

1.5 Thesis structure

Chapter 2 gives an overview of demand side management offering a formal definition, as well as its historical evolution. Relevant work in the domain of model-based assessment of DSM is reviewed and research gaps are identified. The focus is given to the thematic focus of studies as well as the chosen modelling approach. The chapter is concluded by comparing the proposed model to existing approaches and identifying how it can aid in addressing the research gaps.

Chapter 3 describes the process of building the modelling framework ESMA, providing detailed information on the sources of data and the assumptions made in representing the GB electricity system. Justification is given for the overarching agent-based modelling approach, as well as the methods chosen for simulating the electricity generation market and demand side scheduling regimes.

Chapter 4 introduces the simulation scenarios, for which two dimensions are considered: the evolution of the GB electricity system and different DSM regimes. The national scenarios are built based on the Future Energy Scenarios provided by the National Grid, which are adapted in order to arrive with the most optimistic (Two Degrees+) and the most pessimistic (Steady State) cases. Scenarios for DSM regimes include the most decentralised control (implemented by the consumers), semi-centralised control (implemented by the aggregators), and centralised hierarchal scheduling (implemented by the System Operator).

Chapter 5 describes the process of validating the model. ESMA is assessed in terms of recreating historical data and in terms of its agreement with the Future Energy Scenarios developed by the (National Grid, 2017a). At the end of the chapter sensitivity analysis of ESMA to different modelled parameters is performed in order to check that the model functions as it should.

Chapter 6 addresses research question (1) and investigates the issue of consumer herding when end-users schedule demand based on the real time price (RTP) for electricity. This is largely motivated by the UK ‘smart meter’ integration plans, as well as the widely adopted notion that dynamic pricing can encourage end-users to consume electricity more sustainably.

Chapter 6.2 addresses research question (2) and demonstrates the benefits of aggregator-led DSM, as well as the consequences of aggregators using DSM to compete. The value of a centralised hierarchal DSM is demonstrated, whereby the system operator informs the aggregators of the real cost of electricity generation, which then coordinate consumers. The chapter is concluded by a discussion on how the benefits from DSM might be allocated to consumers in the future. Dynamic and flat electricity tariffs are compared, which addresses research question (3).

Chapter 6.3 addresses research question (4), where a totally distributed DSM algorithm is developed. Different DSM regimes are compared in terms of benefits to consumers and the system and the trade-off between system optimality and consumer autonomy in discussed. All analysis in Chapters 6-6.3 is done for the period of 2015-2050 in the Steady State and Two Degrees+. The impact of DSM is assessed in terms system costs, GHG emissions and consumer bills.

Chapter 7 discusses the implications of the results and offers conclusions of this work by evaluating the extent to which the research questions have been answered. The chapter is concluded by addressing the main limitations of the model and suggesting future areas for improvement.

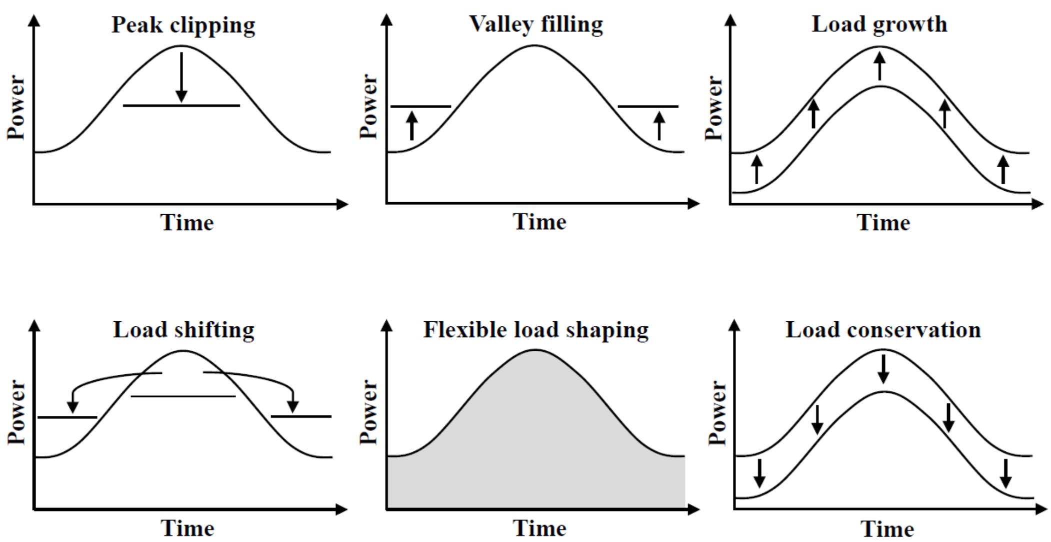
Chapter 2

Literature review

Demand-side management (DSM) refers to the modification of consumer demand for electricity in order to optimise the dispatch of available generation resources, and minimise the cost of maintaining a balanced flow of power in the grid.

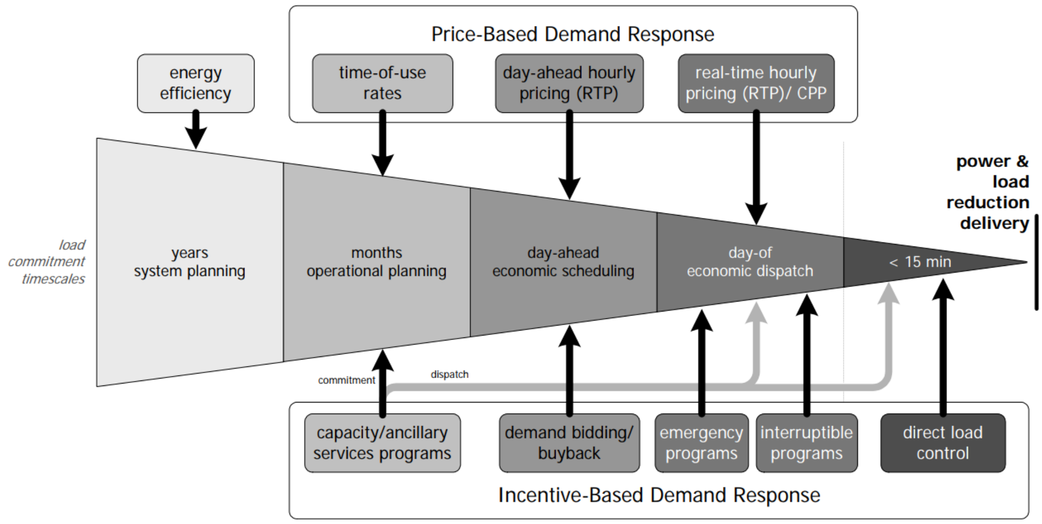
The broader definition of demand side management includes energy efficiency, demand response and on-site generation and storage and can also refer to fuel switching, e.g. using electrical heating as opposed to gas (Warren, 2018). Here, DSM is considered primarily in the context of changing the load profile which is can be categorised based on the objective of doing so (Figure 2.1).

Figure 2.1: Categorisation of Demand Side Management. Source: adapted from (Fleten et al., 2002).



The way in which load altering strategies can be achieved is referred to as a *demand response (DR) program*. Traditionally, DR programs are split into two main categories: price-based and incentive-based (Figure 2.2). Price-based DR programs aim to influence consumer demand through dynamic pricing, such as time-of-use (TOU), real-time pricing (RTP), and critical peak pricing (CPP). These constitute voluntary consumer behaviour meaning that consumers are not obliged to participate. The Economy 7 scheme introduced in the UK in 1978 represents one example of a price-based program. Residential consumers signed up under the scheme are offered a cheaper rate for electricity during the night which constitutes time-of-use (TOU) tariff structure (Ofgem, 2018b; Electricity Council, 1987). Outside the UK, examples include critical peak pricing (CPP) scheme offered by Southern California Edison (SCE, 2017) and a TOU scheme proposed by the national energy utility Eskom in the Western region of South Africa in 1990s (Eskom, 2009).

Figure 2.2: Categorisation of DSM programs in the wider context of the power system operation. Source: (U.S. Department of Energy, 2006).



Participation in incentive-based DR programs obliges consumer to respond in exchange for a financial incentive. These programs include direct load control (DLC), interruptible/curtailable service (I/C), demand bidding, emergency demand response, capacity market, and ancillary services (AS) (Falsafi et al., 2014). Under DLC and I/C programs, consumer demand is directly controlled by a third party (an aggregator or a demand response service provider) which can reduce or interrupt demand on short notice (subject to consumer agreement). Under a demand bidding program, consumers bid their flexibility in the wholesale market and receive a payment from the system operator on delivery of the service at a pre-agreed rate. In the case of emergency demand response, consumers receive a payment for reducing load in an emergency event, the capacity market commits a share of the participant demand flexibility to being used when the system so requires. Examples of international incentive-based DR programs include the Base Interruptible Program offer by The Pacific Gas and Electric Company in California, and the I/C scheme proposed by the Australian Energy Market Operator together with the Australian Renewable Energy Agency in 2017 (Daniel Silkstone, 2017). For a more in-depth discussion the reader is referred to a paper by (Albadi and El-Saadany, 2008) which gives a comprehensive overview.

A note on terminology. In the context of this work, the terms demand response (DR) and demand side management (DSM) are used synonymously since both DSM and DR achieve the same objective of altering demand. Moreover, the two terms are often used interchangeably in the literature (although as pointed out earlier DR is a subcategory of DSM).

2.1 The evolution of DSM

Demand side management has been receiving a lot of attention from academia and industry in the last few decades as a promising solution to balancing the grid, especially as increasing capacities of variable wind and solar are introduced. Yet, the concept of modifying consumption in order to optimise electricity flow in the grid is not new. As a policy tool, it is believed that DSM (formerly referred to as load management) emerged in 1978 under the US Public Utility Regulatory Policy Act (PURPA) triggered by the energy crisis of the 1973 (Eto, 1996; Torriti, 2015). Following the Arab Oil Embargo of OAPEC in 1973-1974 and the Iranian Revolution in 1978-1979, the US energy security was greatly affected. PURPA's purpose was to reduce the country's dependency on imports, mainly through promoting energy conservation and domestic utilisation of renewable energy. However, going beyond the electricity vector the notion of DSM has been around for much longer.

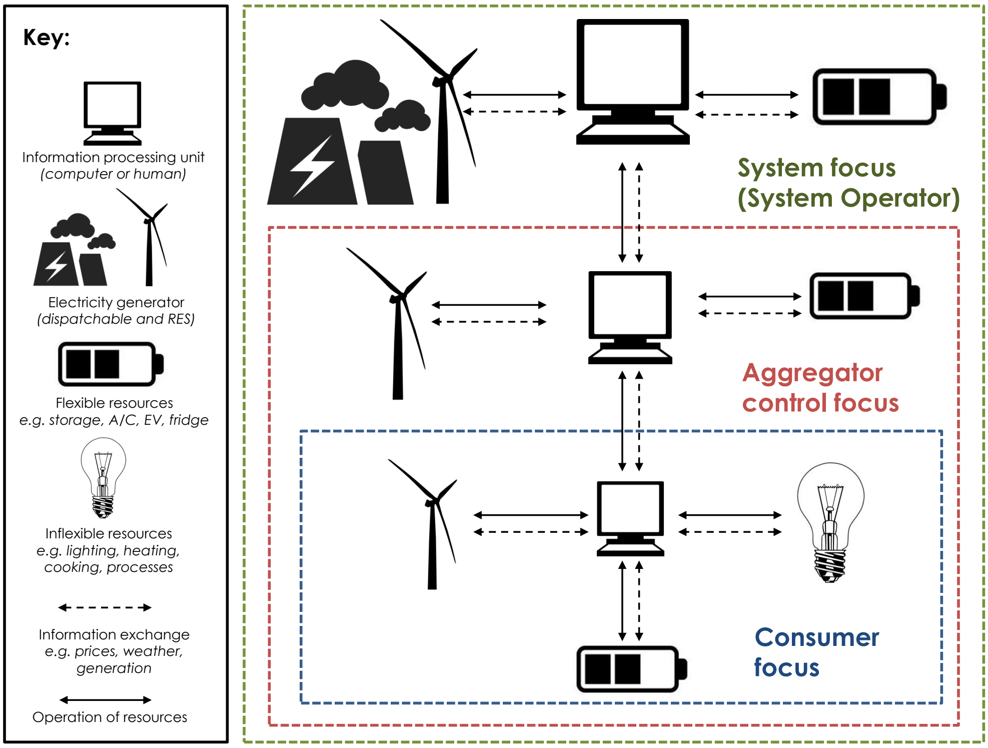
Recent developments in communication and data management tools (smart meters, mobile internet, cloud computing), alongside lowering costs for renewables and storage have reignited academic, industrial and political interest in demand side management, especially in light with the increasing global awareness of climate change issues. The main difference between the traditional and the 'new' DSM schemes is that the latter are becoming more distributed, automated and faster in their implementation as a result of technological progress. More recent work on DSM often assumes the presence of an advanced meter enabling two-way communication between the consumers and the utility, or a smart controller capable of optimising consumer demand based on the information such as the real-time price of electricity (RTP) or a signal from the aggregator. This allows for more elaborate demand response algorithms implemented by the aggregator or consumers themselves - an area of research which has been receiving a lot of attention in the last few decades. Increasing and more accurate data on consumption and generation from renewables, the emergence of new directions for research (machine learning, Big Data, blockchain), coupled with concerns of consumer information privacy, mean that more and more attention is given to making DSM algorithms decentralised and autonomous. That said, some of the earlier works involving local demand scheduling date back to 1980s (Schweppe et al., 1980, 1989), where the authors proposed to use alternating current as a vehicle for real-time pricing in order to signal consumers on how to adjust their demand.

In view with the revived interest in demand side management, a lot of focus by the research community has been given to assessing the impact of DSM on the electricity system. The volume of research in this domain is large, however the extent to which it provides a holistic assessment is arguable. In the following chapter the most relevant work in the domain of model-based assessment of DSM is reviewed with the purpose of identifying state-of-the-art approached in modelling the impacts of DSM and identifying research gaps.

2.2 Model-based assessment of DSM

The literature is classified based on the physical scope of the system considered by the researchers and the objective of the study (Figure 2.3).

Figure 2.3: Classification of literature based on the scope of study.



At the bottom level (*consumer focus*) the literature addresses the impact of DSM on end-users from one or more economic sectors (domestic, commercial, industrial and electric transportation). The focus is primarily on how consumers respond to different DR programs, or on how they should respond. These studies do not explicitly model the system outside of the consumer environment (or do it in a stylised manner) and wider system information such as prices is taken as an external parameter.

The next category of research (*aggregator control focus*) is primarily concerned with developing coordination strategies for distributed energy resources (DERs) in the grid. These maybe individual technologies (e.g. a fleet of plug-in electric vehicles (PEVs), distributed renewable resources (microCHP, solar and small scale wind generators), or consumers which possess one of the earlier mentioned technologies. These studies typically consider a single aggregator coordinating multiple DERs but can also extend to hierarchal coordination, whereby scheduling happens at multiple levels of aggregation (e.g. consumers scheduling devices and the aggregator scheduling consumers). This can be done directly (through physically controlling end-users resources like in the case of DLC) or indirectly through signalling specific system information such as prices. If a study considers an aggregator which is passive (i.e. one which does not make any explicit decisions but acts as a medium for passing information), then it is classified under the 'consumer focus' category since the control is not implemented by the aggregator.

Literature categorised under *system focus* evaluates the impact of DSM in the context of a closed system, meaning that electricity generation (or price formation) and demand are explicitly considered within the modelling framework. Hence, a closed system can represent a small disconnected microgrid, a distribution network, a stylised grid and a whole system representing a country or a region. Typically, 'system focus' assumes centralised coordination of consumer resources initiated by the system operator, which can be done directly (when consumer resources are physically controlled by the SO), or indirectly (when a control signal is sent to consumers straight from the system or via aggregators). In the case when a study tests a control strategy within a closed system, it is first discussed from the point of the coordination approach in the 'aggregator control' category, following which the results of its deployment at the system level are covered in the 'system focus' category. When classifying literature judgement is made based on the level of attention given to developing the control strategy versus representing an existing system. To elaborate, if a study offers an innovative coordination strategy but the context of its deployment is theoretical it is classified as 'aggregator control focus'. On the contrary, if a study pays a lot of attention to modelling an existing system then it is categorised under 'system focus'.

Considering the plethora of academic research carried out in the domain of DSM, the overview of the relevant work is guided by three reviews which perform very succinct classification of the global research on DSM (Yang et al., 2014; Boßmann and Eser, 2016; Howell et al., 2017). Whereas (Boßmann and Eser, 2016) provide a broad overview of modelled-based assessment in relation to different DR programs, (Yang et al., 2014) focus specifically on the mathematical methods used for optimally scheduling electrical vehicles (applicable to any flexible loads), and (Howell et al., 2017) offer a more recent overview of existing work on DSM and discuss new directions of research in the context of the Smart Grid.

2.2.1 Consumer focus

Literature which considers the impact of DSM on consumers, constitutes some of the earliest research and date back to 1980s (Caves et al., 1984; Schweppe et al., 1980). It is observed that earlier work considers consumers as passive entities, whereas later studies model consumers that are proactive with a common objective to cost minimise. This observation is in-line with increasing proliferation of flexible technologies (such as plug-in electric vehicles (PEVs) and heat pumps (HPs)), as well as smart software considered by the authors throughout the research period. These studies can be split into two main groups: those which assess consumer demand response empirically from DSM pilots and those that model consumer behaviour explicitly.

2.2.1.1 Empirical assessment of consumer DSM potential

Empirical assessment of consumer DSM potential includes calculating end-user price elasticities (demand reduction) and cross-elasticities (substitution of peak power with off-peak power) empirically by means of econometric analysis of consumption data obtained from pilot DSM programs.

A significant number of such pilots are performed in the US with the majority focusing on TOU tariffs (Mountain and Lawson, 1995; Baladi et al., 1998; Schwarz et al., 2002; Zarnikau et al., 2007; Woo et al., 2013) and less on RTP (Taylor et al., 2005; Allcott, 2011) and other programs (Faruqui and Sergici, 2011; Wolak et al., 2011; Woo et al., 2013). For example, in (Faruqui and Sergici, 2011) the authors investigate residential consumer response to critical peak pricing (CPP) and peak time rebate (PTR) tariffs under the Smart Energy Pricing (SEP) pilot carried out in

Baltimore and later in Michigan (Faruqui et al., 2014). By using constant elasticity of substitution (CES) approach they are able to estimate consumer price elasticities and conclude that demand can be influenced through dynamic tariffs. From the second study the authors conclude that small commercial and industrial sectors are less price responsive than domestic end-users, which is surprising considering the economies of scale of non-domestic consumers. Larger studies of this type are described in (Filippini, 1995) and (Filippini, 2011), where the author analyses consumer response to TOU tariffs first across 21 Swiss cities during 1987-1990 and then across 22 Swiss cities during 2000-2006. By deploying a number of econometric approaches, the authors demonstrate that peak and off-peak electricity are substitutes, meaning that it is possible to encourage end-users to shift demand from periods of high electricity prices to periods of low electricity prices. The main shortcoming of studies in this group, is that the findings are sample-specific, making it difficult to extrapolate results to larger populations as have been noted by some researchers (Allcott, 2011; Cosmo et al., 2014; Thorsnes et al., 2012). Consequently, the research is limited to past data and to specific regions meaning that the future impact of DSM is left unexplored.

2.2.1.2 Modelling consumer behaviour under a DR program

Some authors opt for simulating consumer behaviour under a DR program using economic models. For example, (Aalami et al., 2010) utilise customer benefit function approach in order to assess the impact of interruption and curtailment (I/C) and capacity market programs in the context of the Iranian Grid. In (Venkatesan et al., 2012) researchers evaluate the benefit of RTP pricing in terms of reducing grid losses during peak hours by deploying the concept of price elasticity matrices, whilst (Matsukawa, 2001) investigates TOU tariffs as a tool to reduce consumer load in Japan through formulating an electricity expenditure function. However, such models tend to utilise historical data for system and consumer parameters including end-user price elasticities and so the issue of sample- and region-specific results is not resolved.

The final group of studies in the 'consumer focus' category, model consumer response to market signals using a bottom-up approach, which allows them to capture the technical characteristics of end-user technologies explicitly. These typically focus on scheduling flexible devices such as fridges (Zehir and Bagriyanik, 2012; Hovgaard et al., 2012), batteries (Schweppe et al., 1989), air conditioning (Ashok and Banerjee, 2003), or a whole smart home (Di Giorgio and Pimpinella, 2012; Houwing and Bouwmans, 2006; Houwing et al., 2007; Han and Lim, 2010; Mohsenian-Rad and Leon-Garcia, 2010) for the purpose of minimising consumer cost of electricity based on the real time prices (RTP). Optimisation is a popular approach for achieving this objective, especially formulated as a linear problem (LP) (Samadi et al., 2010; Roos and Lane, 1998; Conejo et al., 2010) or a mixed integer linear problem (MILP) (Ashok, 2006; Middelberg et al., 2009; Mohsenian-Rad and Leon-Garcia, 2010; Mitra et al., 2012; Di Giorgio and Pimpinella, 2012; Hovgaard et al., 2012; Di Giorgio and Liberati, 2014; Mohsenian-Rad and Leon-Garcia, 2010). Less frequent is a non-linear formulation of the optimisation problem (NLP). Examples includes (Ashok and Banerjee, 2003), where the authors consider optimal operation of a commercial office with air conditioning and (Setlhaolo et al., 2014) who examine the benefits of scheduling domestic appliances under a TOU tariff. Other approaches for scheduling a smart home include evolutionary algorithms such as particle swarm optimisation (Gudi et al., 2012; Yimin Zhou et al., 2014) and genetic algorithms (Khomami and Javidi, 2013; Hsu et al., 2011).

A number of studies utilise agent-based simulation approach combined with optimisation, which allows the authors to decompose consumer actions into their fundamental components and interactions. For example, (Zheng et al., 2014) propose a stochastic agent-based model in order to simulate the electricity demand of an average household and conclude that consumer annual bill reductions from efficient deployment of storage can reach up to 48% (taking into account the capital cost of storage). ABM is a popular approach for modelling consumers with generation and demand resources as a virtual power plant (VPP) (van Dam et al., 2008; Houwing and Bouwmans, 2006; Houwing et al., 2007). For example, in (van Dam et al., 2008) the authors consider a least-cost optimisation scheduling for consumers with micro-CHP and demonstrate that effective coordination of domestic resources can lead to a 2 to 28% reductions in end-user bills.

Comments on the research gaps in the 'consumer focus' category. The main limitation of the models in the 'consumer focus' category is that they ignore the potential impact of a large number of end-users adopting a similar DSM strategy. The main reason is that the consumer system is considered in isolation, meaning that their actions are not evaluated in terms of how they affect the market. As a consequence, the benefits of DSM are typically evaluated from the view point of a single cost minimising consumer, who benefits from shifting demand from periods of expensive electricity to periods of cheap electricity. In reality, wholesale electricity prices depend on the demand for power aggregated across all consumers in the market. Hence, if a large enough number of end-users shift demand based on the same price signal this could lead to the creation of new demand peaks. This effect is known as *herding* or *avalanche* and constitutes one of the main risks of autonomous response of consumers to centrally-determined market signals such as real time prices.

Some studies already provide evidence that there might be issues with consumers scheduling demand based on the same price signal. For example, in (Ericson, 2009) the authors investigate the impact of a DLC program tested on 475-household system during a 180-day trial in Norway. The study found that although demand is notably reduced during disconnection (on average 0.5 kWh/h decrease per household), an hour following the event demand goes up indicating a potential for consumers to herd. Another example is (Gottwalt et al., 2011), where the authors report that scheduling domestic appliances based on time variable prices can produce an avalanche effect and the creation of new demand peaks.

One way to solve the issue of consumer herding is through an aggregator-controlled DSM. The next section discusses different approaches adopted by researchers which achieve this objective.

2.2.2 Aggregator control focus

Research in the ‘aggregator control focus’ category primarily investigates different methodologies for effectively scheduling distributed energy resources (DERs). A typical set-up of the system in these studies includes a single aggregator coordinating a pool of DERs (such as electric vehicles (EVs), heat pumps, or smart consumers), however it can extend to hierarchal control at multiple network levels. System components such as the market or a System Operator tend to be more stylised in their representation, since the focus is on devising new control methodologies rather than recreating an existing electricity system. The literature in this category can be split depending on whether the demand scheduling approach considered is centralised or a decentralised.

Centralised versus decentralised coordination. In a conventional sense, incentive-based programs (such as DLC and I/C) represent centralised coordination, since the aggregator has physical control of consumer resources and price-based programs (RTP,TOU) constitute indirect control. However in the context of the literature review, the type of coordination is defined depending on how it is mathematically formulated. To elaborate, a study may not explicitly mention that the consumers operate under an incentive-based program but the problem will be formulated as a global optimisation problem for the aggregator (assuming that it has access to all of consumer information). This would constitute centralised scheduling since in the context of the model consumers have no choice but to respond to aggregator signalling. Some coordination approaches do not consider an aggregator at all and consumers schedule their resources completely autonomously based on the information received from its peers of local information (e.g. system frequency). As a result the following definitions are adopted:

Centralised coordination - on scheduling the aggregator (which could represent a utility a demand response service provider or a System Operator) has total knowledge and control of consumer resources. This may be explicitly formulated as an incentive-based program or implicitly assumed through mathematical formulation of the problem, e.g. global optimisation.

Decentralised coordination - consumers schedule own demand autonomously depending on the signal (e.g. prices or system frequency) communicated by the aggregator, the market, its peers (or neighbours), or received locally (e.g. system frequency).

2.2.2.1 Centralised coordination

Centralised coordination is the historically common approach for optimally scheduling DERs. Studies deploying centralised coordination typically look at scheduling a fleet of flexible demand resources such as PEVs (Sundstrom and Binding, 2010; Sortomme et al., 2011), heat pumps (Wang et al., 2012), thermostatically controlled loads (Callaway, 2009; Lu and Zhang, 2013; Kundu et al., 2011), or a pool of smart consumers (Zugno et al., 2013; Feuerriegel and Neumann, 2014) for the purpose of offering balancing services to the grid in order to reduce system cost of for the purpose of minimising the cost of purchased electricity by the aggregator (often representing a utility) from the wholesale market .

A large number of studies deploying centralised coordination consider mathematical optimisation for this purpose. For example, non-linear programming (NLP) has been used to study the impact of DR programs on the distribution grid (Acha et al., 2010; Clement-Nyns et al., 2010; Faria and Vale, 2011) or to improve load following (Mets et al., 2012, 2010). Another example includes (Doostizadeh and Ghasemi, 2012) where the authors come up with a novel RTP policy and demonstrate that it can result in lower system losses, reduced system demand peak and higher load factor (calculated as a ratio between average to peak demand). Linear programming (LP) is deployed by (Feuerriegel and Neumann, 2014) in order to measure financial benefit of DR programs to the retailer and in (Sundstrom and Binding, 2010, 2012) to analyse the potential of avoiding grid congestion and voltage problems by means of scheduling a fleet of electric vehicles.

Optimisation is a classic approach for scheduling DERs in a microgrid (Lasseter, 2002) for the purpose of optimising local resources and minimising the cost of operation (Geidl and Andersson, 2007; Lee and Kim, 2013; Kuznetsova et al., 2014; Rivarolo et al., 2013; Quiggin et al., 2012; Stluka et al., 2011; Morais et al., 2010;

Chen et al., 2014). For example, in (Rivarolo et al., 2013) the authors use optimisation in order to make better use of multiple energy sources in a microgrid at the University of Genoa. The paper demonstrates the importance of an appropriate storage system when it comes to maximising the utilisation of renewable energy. Others assess microgrid scheduling in terms of the technical characteristics. (Kuznetsova et al., 2014) use agent-based modelling in combination with robust optimisation in order to demonstrate the benefit of scheduling resources for the purpose of improving microgrid reliability and lowering the cost of its operation.

Limitations of centralised control. Centralised control is the best approach for offering optimal or near optimal solution and constitutes a very good choice in some cases, e.g. a small microgrid. However, its main limitations is that it requires consumers to give up control and information of their resources, which may not be appreciated by some end-users, especially in the residential sector (Medina et al., 2010; Rahimi and Ipakchi, 2010). Another shortcoming is scalability, since centralised coordination requires communication of a large number of technical parameters from various DERs to the aggregator. Hence, as the number of flexible consumer resources increases it becomes more computationally challenging for the aggregator to arrive with the solution (Sonnenschein et al., 2014).

2.2.2.2 Decentralised coordination

Decentralised coordination typically assumes indirect control of smart load agents using a signal like real time pricing or system frequency. However, communicating the same signal to a sufficiently large population of agents may lead to consumers ‘herding’ as they adopt similar optimisation strategies. Hence, the challenge of decentralised control lies in steering self-interested agents towards global optimum without explicit control by a central entity.

A number of papers deploys *iterative coordination*, whereby an aggregator negotiates the demand profiles with a pool of consumers (or flexible demand units) over a number of iterations until the system converges. Convergence is achieved by either consumers or the aggregator adjusting (or learning) the strategy over the course of the negotiations. For example, in (Vytelingum et al., 2010; Voice et al.,

2011) the authors propose an algorithm in which consumers schedule demand based on the real time price in order to cost minimise. In order to avoid large swings in system demand, end-user response is supressed through a damping term which penalises them for shifting demand too much from the previous schedule. As a result of this algorithm, consumers slowly adapt to the market and reach the point of Nash equilibrium. In the context of the UK electricity market, the authors demonstrate that the algorithm leads to a 17% reduction in the system peak and up to 6% decrease in carbon emissions. In (Ramchurn et al., 2011) the same algorithm is extended to include information of renewable generation in the system by means of introducing carbon-based retail tariffs. In (Gan et al., 2013) the authors apply iterative coordination for scheduling PEVs, but in contrast to (Ramchurn et al., 2011; Voice et al., 2011) where each iteration represents a day, all negotiations between EVs and the aggregator take place during the day-ahead scheduling. Using a similar approach, in (Li et al., 2011a; Guo et al., 2013) the researchers demonstrate that theoretically dynamic pricing can be structured in a way as to ensure optimal result for both the consumers and the utility. In contrast to the above studies, (Yousefi et al., 2011) presents an approach whereby the aggregator learns the price signal to send to consumers who then cost minimise.

Randomised control is an alternative approach for coordinating flexible loads in a decentralised manner. Randomisation can be achieved in two ways: consumers reacting differently to the same signal or reacting in the same way to different signals. The former case includes stochastic load response and is typically deployed for the purposes of frequency control with a fleet of flexible resources such as electric vehicles (Callaway and Hiskens, 2011; Meyn et al., 2015; Zhou and Cai, 2014) or thermostatically controlled loads (Tindemans et al., 2015; Hao et al., 2014). However, this approach is tailored to managing a fleet of similar type of flexible resources which can stochastically switch on and off or react very quickly, and so becomes inapplicable to more complex demand scheduling. In the second case of randomised control the aggregator calculates different signals for each consumer which allows its application to coordinating a pool of smart consumers (Boait et al., 2007; Snape et al., 2013; Mohsenian-Rad and Leon-Garcia, 2010) or more generic flexible loads (Papadaskalopoulos and Strbac, 2015). In (Ghasemi et al., 2016), the authors use a two-point estimate method in order to model uncertainties associated with renewable generation from wind and calculate optimal prices for cost minimising flexible end-users. However, the necessity of having a central entity which is able to calculate different signals introduces the issue of scalability as the number of consumers increases.

Market-based coordination allows consumption and generation agents to negotiate settlement in a decentralised manner through interactive bidding into the market, which is overseen by a third party (an auctioneer) that determines equilibrium prices and ensures network balance. For example, (Motto et al., 2002) propose a decentralised electricity market whereby supply and consumer agents respond to real-time prices and optimise their surpluses. (Ghijsen and D'hulst, 2011) apply market-based approach to evaluate its effectiveness in the case of EV charging and specifically look at the effect on peak voltage. The main limitation of having consumers bid into the market is that it introduces uneven opportunities, since the scheduling is based on the order in which end-users react. Therefore, those which bid quicker get the cheapest power, which solves the problem of resource allocation but not necessarily in the fairest manner with regards to consumers. It is possible to imagine that end-users with better technology would be able to make faster and more accurate decisions. Yet, the access to technology is closely linked to the wealth of a particular end-user, which implies that those with more financial freedom would be able to obtain cheaper electricity.

Extensive work on market-based coordination has been carried out at the Energy research Centre of the Netherlands (ECN), where the researchers have developed a hierarchal framework for market-based coordination in the context of a multi-agent system (MAS) (Kok et al., 2005, 2010). A multi-agent system (MAS) is a software system implemented as a collection of interacting autonomous agents (Newell, 1982). In the context of MAS, an agent corresponds to any self-contained software program that is representative of something (e.g. washing machine, EV) or someone (e.g. prosumer, smart home) (Kok et al., 2010). These software agents are equipped with some specific rules on how to react to system signals and the response (bidding into the virtual market) happens automatically without human intervention (but taking into account human preferences of usage). The framework has been tested in a number of scenarios and the technology is now commercially available[1]. MAS is also a popular approach for scheduling microgrids in a decentralised manner (Wernstedt et al., 2007; Lagorse et al., 2010; Booij et al., 2013; Gonzalez De Durana et al., 2014). For example, (Wernstedt et al., 2007) use it to dynamically schedule District Heating Systems and demonstrate the positive effect it can have on shaving demand peaks without affecting the quality of service for consumers.

Other approaches for decentralised coordination include *game theory*. An interesting finding is made in (Zugno et al., 2013), where the authors model aggregator-consumer interaction using as a Stackelberg game (where players represent leaders and followers (Von Stackelberg, 2011)). The study finds that under the dynamic pricing scheme, the financial benefits are not distributed fairly between the retailer and consumer indicating a conflict of interest between the two types of stakeholders. This is an important finding and one which is not mentioned by many researchers, considering its importance with regards to fair allocation of benefits from DSM. Stackelberg game approach is also used in (Dai et al., 2017; Han et al., 2017), where the authors examine DSM in the context of a competing retail energy market. In both studies researchers find that a well-designed RTP tariff structure can benefit energy retailers as well as consumers. Game theoretic approach is used in (Amir-Hamed Mohsenian-Rad, Vincent W.S. Wong, Juri Jatskevich, Robert Schober, 2010), where the authors come up with a smart billing strategy which ensures that the system converges when consumers optimise on the price independently. However, the authors assume that each consumer has demand information of the rest of the market, which might be difficult to implement in the real world. Moreover, the algorithm is tested with ten consumers over twenty-two iterations,

[1] See `http://flexible-energy.eu/powermatcher/` for more information.

which questions its scalability to a system of millions of end-users.

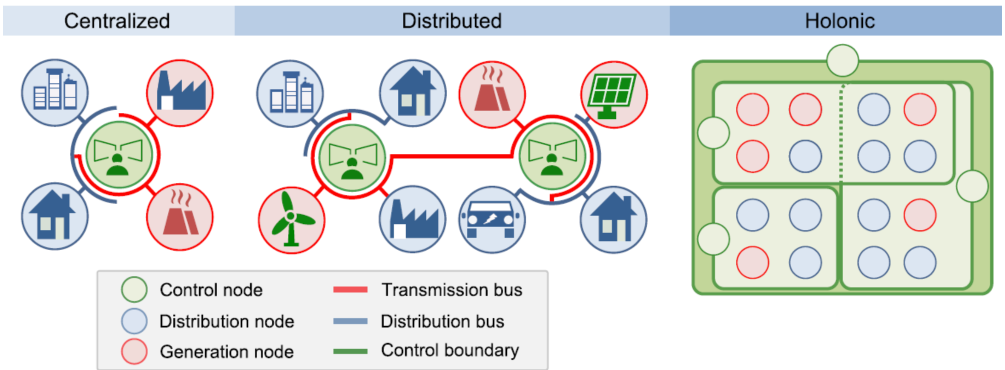
Some researchers opt for *heuristic methods* of scheduling flexible resources. Water-filling, whereby the surplus demand is shared across consumers in a similar way to the water filling a vessel, is one such example. In (Mou et al., 2015) the authors apply this approach in order to flatten aggregated demand from a fleet of PEVs. As PEVs schedule autonomously, their aggregate demand is shared in the network which leads to a valley-filling effect. Other examples include (Vandael et al., 2011), where the grid imbalance is allocated to electric vehicles depending on the time they leave and their earlier submitted intentions to charge. In (Changsun Ahn et al., 2011) the authors discover that charging power is dependent on the state of charge of the PEV battery and the availability of renewable energy. As a result of these findings, the aggregator is required to signal consumers only once avoiding the need for bi-directional flow of information. A similar method is offered in (Zhang et al., 2014), where the researchers analytically deduce optimal dynamic prices which lead to a valley-filling effect when PEVs cost minimise.

Finally, a group of studies develop decentralised coordination strategies which do not require an aggregator at all. For example, in (Rahbari-Asr and Chow, 2014) the authors propose a cooperative distributed algorithm for scheduling electric vehicle charging. More recently research in decentralised DSM without the need for an aggregator has been focusing on blockchain-enabled peer-to-peer trading between consumers (Li et al., 2017; Wu et al., 2017) and machine learning-inspired algorithms enabling consumers to adjust to the market autonomously (Lopez et al., 2018). However, these studies have been tested in a limited setting either for just one type of technology (e.g. PEVs) or for a small pool of consumers. For one, an autonomous system without a central coordinator would require a secure and reliable communication infrastructure between consumers. Hence, the extent to which these methods can be applied in a realistic setting has not been fully evaluated.

2.2.2.3 Holonic coordination approach

More recently, researchers consider DSM in the context of a holonic energy system (Ounnar et al., 2013; Vlad et al., 2014; Lubomir et al., 2014; Pahwa et al., 2015). A 'holon' represents something that is a whole and a part, meaning that a holonic energy system is a system of systems. This representation means that coordination is neither centralised not distributed (Figure 2.4). For example, in (Pahwa et al., 2015) the authors combine a holonic representation of the energy system with MAS approach in order to provide a design for distribution system operation. They are able to demonstrate that this approach offers an effective design to control reactive power in a distribution grid with high PV penetration. Whilst holonic paradigm offers a promising approach to link together the different methodologies explored at various levels of hierarchy in the energy system, the research is still at the conceptual level.

Figure 2.4: Comparison of centralised, distributed and holonic system representation. Source: (Howell et al., 2017).



Comments on the research gaps in the 'aggregator control focus' category. Literature in the 'aggregator control focus' category covers very innovative and useful methods for coordinating consumer demand, especially when carried out in a decentralised manner. However, much to do with the focus of research placed in this category, its main limitation is that the testing tends to be carried out in an isolated setting. Moreover, consumers are often modelled as homogenous which enables the authors to formulate the coordination problem more elegantly. For the same reason electricity generation and pricing are taken as exogenous parameters. As a result, the impact of DSM is not evaluated in the context of the whole system. For example, typical outcome reported by researchers includes financial benefits to the aggregator or its consumers. In reality, aggregators (especially those representing utilities) compete in the wholesale electricity market. Thus, it is possible to imagine that they will use DSM as a tool to purchase cheap electricity for themselves which can lead to aggregator herding. In fact in (Prüggler et al., 2011), the authors find that strategic manipulation of demand by vertically integrated utilities can result in the long term price increases and higher electricity bills for customers. This suggests that in the future stricter regulation of utility activities might be required to avoid such problems.

Following the research gaps identified in this category, in the next section the focus is given to those studies which evaluate the impact of DSM in the context of a closed system.

2.2.3 System focus

As the name suggests, 'system focus' category incorporates all studies which evaluate the impact of DSM at the system level. A distinguishing feature of these studies is that they consider a closed or self-sufficient system, meaning that electricity generation (or costs) are explicitly modelled.

2.2.3.1 DSM and generation

A popular focus of research in this category is assessing the impact of DSM on the generation dispatch (Chen et al., 1995; Kirschen et al., 2000; Zhong et al., 2015; Zakariazadeh et al., 2014; Malik, 2001), especially in the context of unpredictable renewable generation (Sioshansi, 2010; Broeer et al., 2014). A common approach adopted by researcher is to consider load scheduling as part of the unit commitment model formulated as an optimisation problem. For example, in (Sioshansi, 2010) the authors demonstrate how including DSM in the day-ahead generation scheduling can reduce redispatch costs and improve reliability of a grid with uncertain generation from wind. Other reported benefits of DSM include avoided voltage violations (Papaioannou et al., 2013) and reduced cycling costs of power plants (Malik, 2001). The main limitation of these studies is that scheduling is formulated as an optimisation problem which corresponds to central coordination. This means that the demand side interactions are not captured. In addition to this, the demand side is often modelled as a single load curve, thus limiting the extent to which these studies constitute whole system assessment of DSM.

Another popular direction of research in this group of studies is examining the impact of DSM on the energy mix (De Jonghe et al., 2012; Keane et al., 2011; Finn et al., 2011; Pakka et al., 2013). A common conclusion of this work is that DSM can lead to improved balancing of intermittent generation energy and consequently lead to a higher installed renewable capacity. However, in (De Jonghe et al., 2012) the assessment is done for a single day, whereas (Broeer et al., 2014) focus on one historical year. (Keane et al., 2011) and (Finn et al., 2011) perform analysis for the future year of 2020 but system assessment is done using linear optimisation and once again stakeholder dynamics are not captured.

2.2.3.2 Benefits of flexible technologies

Another focus of research in this group is on assessing the benefits of specific technologies such as dishwashers (Finn et al., 2013), EVs (Bach et al., 2010; Babrowski et al., 2014; Lund and Kempton, 2008; Finn et al., 2012), heat pumps (Wang et al., 2012), or a combination of these (Papadaskalopoulos et al., 2013; Fehrenbach et al., 2014) on balancing the grid. For example, in (Papadaskalopoulos et al., 2013) examine the capacity in which electric vehicles and heat pumps can help balance the grid in the UK and find that DSM can lead to significant reductions in electricity generation costs. However, by considering only a few technologies these studies do not capture the full scope of system flexibility and hence fail to evaluate DSM potential fully. Moreover, these studies tend to represent consumer demand in an aggregate manner (Fehrenbach et al., 2014), therefore losing critical end-user interactions.

2.2.3.3 Real world implementation of DSM coordination strategies

A few papers report on the results of pilots which test a specific coordination mechanism in an existing electricity system. For example, (Morais et al., 2010) deploy an MILP scheduling strategy in managing a real world microgrid located at Budapest Tech. The authors conclude that effective scheduling of storage can maximise the utilisation of renewable energy (wind and solar) which optimises the use of other fuels in the microgrid. Another example includes (Roossien et al., 2008), where researchers demonstrate the effectiveness of the PowerMatcher concept in managing a cluster of households with microCHP in the Netherlands. They conclude that the algorithm can lead to a 30-50% reduction in peak load without affecting consumer comfort. However, both of the above examples constitute very small systems and so wider implications of these approaches are not evaluated.

2.2.3.4 DSM and market

A number of studies assess DSM in terms of its effect on electricity market characteristics. For example, (Joung and Kim, 2013) examine the impact of load flexibility on strategic price formulation of generators, whereas (Su and Kirschen, 2009) propose new market clearing mechanism and (Tanaka, 2006; Nikzad et al., 2012) develop new pricing policies. However, they do not demonstrate the implication of these findings on a system-wide level and therefore do not constitute a holistic assessment of DSM. In (Dou and Liu, 2014) the authors deploy a market-based coordination algorithm in order to demonstrate how DSM can improve the reliability of the grid as well as lead to lower system costs and emission levels. (Moghaddam et al., 2011) use the concepts of consumer benefit function and consumer price elasticities for the purpose of evaluating how different demand response schemes (i.e. TOU, CPP, RTP, I/C, DLC) affect the market from the perspective of consumers, utilities and the system operator. Yet, the authors perform the analysis using historical load profile and prices from the Iranian electricity grid on an annual peak day. The main shortcoming of the models placed in the 'system focus' group is that they consider a stylised representation of the electricity system, either by aggregating the demand or the supply sides. They also tend to consider a very short period of simulation (e.g. a day). As a result, these studies hide stakeholder interactions and tend to evaluate the impact of DSM in a theoretical manner.

2.2.3.5 Whole system assessment of DSM

A group of studies have been identified to carry out the most holistic assessment of DSM. For example in (Fehrenbach et al., 2014), the authors use TIMES modelling framework in order to assess the economic potential of load management performed by VPPs (representing residential consumers with micro-cogeneration plants, heat pumps and thermal storage) until 2050. They conclude that effective load management can contribute to a more sustainable energy mix (e.g. oil-fired generators are phased out) as well as significant reduction in CO2 emissions. Similar studies are performed for Portugal (Moura and de Almeida, 2010) and Portuguese Island of Azores (Pina et al., 2012), UK (Strbac et al., 2012), Germany (Klobasa, 2010) and the European Union (Papagiannis et al., 2008). However, all of the above studies use system-wide optimisation based on objectives such as least cost or minimum emissions and so stakeholder interactions are not explored.

Agent-based modelling (ABM) offers an alternative approach. For example, in (Valenzuela et al., 2012) researchers use ABM to assess the impact of DSM on market prices, peak demand, consumer energy costs, and producer revenues in South Korea. However, the study utilises historical end-user price elasticities in addition to the assessment being done for one year. (Ramchurn et al., 2011) and (Vytelingum et al., 2010) use ABM to model the impact of DSM in the UK, but they only consider residential consumers. Another UK study is performed in (Roscoe and Ault, 2010), where the researchers deploy a combination of analytical methods including a probabilistic approach for modelling flexible demand and modelling the price curve as an exponential function. However, the assessment is performed for a 6-week period, considering only residential DR as well as using historical electricity prices.

Comments on the research gaps in the 'system focus' category. The literature in the 'system focus' category constitutes very insightful and interesting research. However, it is found that studies which focus on the methodological component of DSM implementation fail to assess it in the context of the wider system scope, whereas research focusing on the representation of an existing system does not address the heterogeneity of different stakeholders and their interactions.

This is either because assessment is performed on a test system (Falsafi et al., 2014; Wang et al., 2013), a small part of the network (Logenthiran et al., 2011; Valenzuela et al., 2012; Zakariazadeh et al., 2014; Boait and Snape, 2014), at a very coarse temporal resolution (Papagiannis et al., 2008), or statically without capturing the dynamics of stakeholder interactions (Shaw et al., 2009). A limited number of studies assess the future impact of DSM considering a variety of different consumers. However, few go beyond 2020 (Klobasa, 2010; Moura and de Almeida, 2010; Pina et al., 2012; Finn et al., 2012) and even fewer beyond 2030 (Strbac et al., 2012; Fehrenbach et al., 2014). In addition to this, long term analysis tends to be performed using system-wide optimisation which does not capture dynamic stakeholder interactions. An alternative to this are ABM models, but these only consider the residential sector and do not assess DSM impact in the future (Ramchurn et al., 2011; Vytelingum et al., 2010).

2.2.4 A note on dealing with uncertainty

One important issue with modelling energy systems is uncertainty in predicting supply from renewable resources (especially wind) and demand (which is becoming more unpredictable). There are two main approaches adopted by research to address this: *stochastic programming* and modelling close to *real time*.

In contrast to deterministic mathematical programming, stochastic programming involves formulating an optimisation problem in terms of expected values and probabilistic constraints (Boyd and Vandenberghe, 2010). Stochastic programming is often applied when the authors consider renewable generation (Fleten et al., 2002; Falsafi et al., 2014; Keane et al., 2011) or to accommodate unpredictable demand (Zheng et al., 2014; Deilami et al., 2011). For example, in (Keane et al., 2011) the approach is used to model unit commitment with RES and load forecasts uncertainty, whereas in (Zheng et al., 2014) the authors develop a stochastic demand model for a smart home management system.

In order to reduce uncertainty some researchers adopt real time (or near real time) optimisation in order to minimise the time between performing scheduling and the event taking place. For example, in the case of wind generation the supply can be predicted fairly accurately up to 4 hours ahead (Milligan et al., 2009). Hence, scheduling loads with wind predictions of 2 hours ahead will be a lot more accurate than scheduling 24 hours ahead. Real-time scheduling is also intuitively appealing in the context of individual device management and hence a popular approach for scheduling randomly connecting electric vehicles. For example, (Deilami et al., 2011) develop real-time smart load management control strategy for coordination of PEV charging based on real-time (5 mins) minimisation of total cost of energy generation by incorporating time varying market energy prices and PEV owner preferred charging time zones based on priority selection. Other examples of on-line load scheduling include (Li et al., 2011b; Ma et al., 2015; Turitsyn et al., 2010).

In this work the second approach for dealing with uncertainty is chosen. As described in Chapter 3, the market reschedules generators in real time following the system operator obtaining the final information on system demand. In contrast to stochastic programming, this approach is much quicker in its implementation since it does not require a probabilistic formulation of the problem. This allows the program to run faster (critical for long-term system modelling), whilst still preserving the objective of the work - to evaluate the financial impact of demand side management on the system in terms of the cost of generating electricity.

2.3 Conclusions of literature review

Following the literature review, the following research gaps are identified in the domain of model-based assessment of DSM:

1. Studies which focus on demand scheduling mechanisms tend to test them in an isolated or stylised setting, e.g. only considering a pool of consumers being coordinated by a single aggregator. As a consequence the results are taken outside of the wider system context.

2. Models which consider realistic simulation settings assume perfect consumer behaviour formulated as a large optimisation problem. As a result different stakeholder interactions are not considered and issues like consumer herding or aggregator competition in the context of DSM are not explored.

3. A limited number of works focus on the future impacts of DSM. Those that do often consider a limited number of flexible technologies or deploy system-wide optimisation which ignores demand-side interactions.

4. The majority of studies focus on the residential sector leaving the impact of DSM on non-domestic consumers unexplored. Moreover, there is a lack of literature which compares the impact of DSM on different consumers types, i.e. with different resource accessibility.

In terms of the most relevant research in the domain of DSM assessment in the context of the UK, a number of studies have been identified which are summarised in Figure 2.5. Important contributions have been made by a team of researchers at the De Montfort University, who consider a number of topics concerning the transition of the national electricity system towards a ‘Smart Grid’, such as integration of distributed generation, electrification of transport and active consumer behaviour (Snape et al., 2015; Boait and Snape, 2014; Pakka et al., 2013). However, the studies have so far focused on the residential sector only and have not explored issues like consumer herding or aggregator competition. Researchers at the Southampton University have provided valuable input in terms of coming up with decentralised coordination approaches which help to overcome consumer herding (Voice et al., 2011; Ramchurn et al., 2011). However, the authors only consider the residential sector and test scenarios in a stylised setting using past data. A study prepared by a team of researchers from Imperial College in collaboration with NERA Consulting (Strbac et al., 2012), constitutes one of the most holistic assessment of DSM in the context of the UK. However the authors perform system-wide optimisation and so stakeholder interactions are ignored. Although the study provides some very valuable and interesting finding, some of the risks of DSM such as herding or aggregator competition are not considered.

In order to address existing research gaps this work proposes an Energy System Management Agent-based model (or ESMA), which will fulfils the following criteria (see last row of table in Figure 2.5):

1. Explicitly consider generation and costs from dispatchable and renewable energy resources;

2. Include heterogeneous consumers representing all economic sectors with different combination of flexible and inflexible resources;

3. Explore future scenarios as far as 2050 for the British electricity system ranging from the most pessimistic to the most optimistic one;

4. Model interactions between consumers and aggregators and explore the impact on the system when they pursue selfish objectives;

5. Address the issue of electricity cost allocation.

2.3.1 Open source modelling platforms

A number of open source whole system energy models have been identified during the literature review. For long-term analysis researchers tend to use model like TIMES (bottom-up least cost optimization model)(ETSAP, 2018) or EnergyPLAN (a simulation model which optimises the operation of a given system based on the input parameters) (Sustainable Energy Planning Research Group at Aalborg University, 2018). However, these types of models do not capture dynamic stakeholder interactions, for which reason they would be unsuitable in being used in the context of an energy system where stakeholders are able to make decisions based on dynamic system parameters. Agent-based modelling has been identified as a suitable approach for capturing such dynamic interactions. A number of open source ABMs have been identified (Argonne National Laboratory., 2018; Grozev et al., 2018; De Montfort University, 2018; Li and Tesfatsion, 2011). For example CASCADE (developed at the De Montford University) (De Montfort University, 2018) was created especially to capture the complexity of the British electricity system. One of the shortcomings of using a ready-made model is that the behaviour of agents amongst each other and the system is predetermined by the original model developer. This can make it difficult to introduce changes at the level of agent interactions. The objective of this research is to explore the sensitivities of the British electricity system to different regimes of DSM. In order to fully realise this objective it has been decided to create a new model, incorporating relevant ideas and methods discovered during the literature review.

Figure 2.5: Comparison of the most relevant existing models and identification of research gaps.

Reference	Modelling approach	Temporal scope		Spatial scope	Electricity generation		Stakeholders			Consumer sectors				Stakeholder interactions		Flexible technologies considered						Cost allocation
		Resolution	Simulation period		Dispatch	RES	Con	Agg	SO	Dom	Com	Ind	Trans	Con comp.	Agg comp.	EV	EH	WA	TES	ES	CA	
Strbac et al., 2012	LCO (TIMES)	1h	2020-2050	UK as part of EU	✓	✓	✓		✓	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓	
Vytelingum et al., 2011	ABM, game theory	30s	2009 (partially)	UK			✓	✓		✓				✓	✓					✓		
Voice et al., 2011	ABM, game theory	30s	2009 (partially)	UK			✓	✓		✓				✓	✓					✓		
Ramchurn et al., 2011	ABM	30s	2009 (partially)	UK		✓	✓	✓		✓				✓	✓					✓		✓
Roscoe & Ault, 2009	Sim	30s	2008 (partially)	UK		✓	✓		✓	✓	✓	✓					✓	✓	✓		✓	✓
Boait et al., 2013	ABM (CASCADE)	30s	2020	UK	✓	✓	✓	✓	✓	✓				✓		✓	✓					
ESMA	**ABM**	**1h**	**2015-2050**	**UK**	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓		✓

Key: LCO=least-cost optimisation, ABM=agent based modelling, Dispatch=dispatchable generators, RES=renewable generators, Con=consumer, Agg=aggregator, SO=system operator, Dom=domestic, Com=commercial, Ind=industrial, Trans=transport, comp.=competition, EV=electric vehicle, EH=electric heating (includes cooling), WA=wet appliances, TES=thermal energy storage, ES=electrical storage, CA=cold appliances

Chapter 3

Methodology: building ESMA

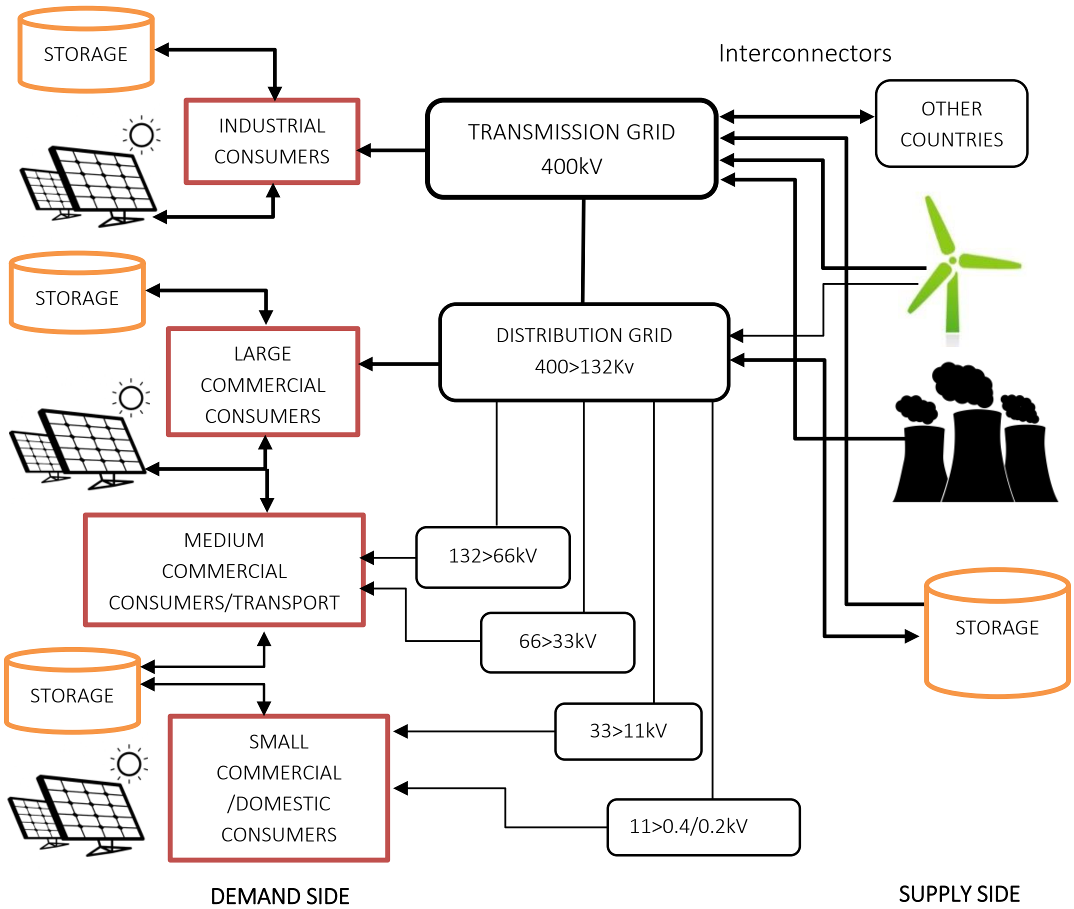
Following the identification of research gaps in Chapter 2, a model for Electricity System Management using an Agent based approach (or ESMA) is proposed, which includes heterogeneous consumers (representing domestic, commercial, industrial and transportation sectors), aggregators (representing entities which can pool consumers and trade power in the wholesale market), the system operator (responsible for overseeing the balance of electricity in the grid) and the market (representing a pool of transmission level generators and pumped storage). The main feature of the model is its capability to simulate different regimes of demand side management (DSM) ranging from totally decentralised (performed by consumers) to totally centralised (performed by the system operator).

The following chapter covers the methodology for building ESMA focusing on justifying model assumptions, selecting model actors and choosing methods to simulate their interactions. The British electricity system is taken as a case study, since it represents a good example of a power system undergoing decentralisation. However, the model is not country specific and can run with other data.

3.1 Overview of the British electricity system

The schematic of the British electricity system is portrayed in Figure 3.1. It consists of supply and demand sides linked together by the transmission and distribution network. The supply side contains sources of electricity generation, such as renewables (e.g. wind and solar) and dispatchable power plants (e.g. coal and gas generators), storage (such as pumped) and interconnectors to other countries. The demand side represents consumers from four economic sectors (domestic, commercial, industrial and transport) in possession of electricity generation technologies and storage. The transmission and distribution networks, which operate at different voltage levels, impose physical network constraints on the power flow through the system.

Figure 3.1: Graphical representation of the British electricity grid.



3.1.1 Electricity wholesale market

In deregulated electricity markets, such as in the case of the UK[1], electricity is largely traded in the wholesale market, which allows large consumers (e.g. industrial or large commercial) or energy utilities (companies which retail power to pools of smaller consumers) to purchase power from electricity generators.

Wholesale electricity trading can be split into over-the-counter (OTC) and exchange markets. OTC trades tend to be for delivery further into the future (months and even years ahead), whereas exchange trades are typically for short term delivery (intraday and day-ahead). In the UK (like many European markets), the majority of power is traded in the OTC market, where parties negotiate volumes and prices for electricity in private (Elexon, 2017b). Trading is carried out on three main exchanges: APX Group[2], Nord Pool (or N2EX)[3] and the Intercontinental Exchange (or ICE) [4]. In contrast to the OTC market, exchange trades come in standardised volumes and the prices are made openly available. OTC prices are closely aligned with exchange prices, since any arbitrage opportunity would be quickly exploited by the market (Rademaekers et al., 2008). Both OTC and exchange markets include deals which are executed by traders not for physical delivery but for realising an arbitrage opportunity. In this work only the market for physical delivery is considered.

3.1.2 Balancing the grid

Unlike other commodities electricity in the grid must be balanced in real time, meaning that whatever is being supplied into the grid must be taken out at the same time, since power is still expensive to store. System balance is measured by its frequency, which must stay within 1% of 50Hz (National Grid, 2016). Not enough generation (or too much demand) will lead to the system frequency drop, and a big drop in frequency can lead to a black-out. Too much generation (or not enough demand), will increase system frequency and could result in the damage to the grid.

[1]Market arrangements are considered in the context of the United Kingdom, whereas the model is built for the British electricity network only since Northern Ireland has a separate grid. Hence, the data is taken to represent the British grid and excludes Northern Ireland.

[2]See `https://www.apxgroup.com/`

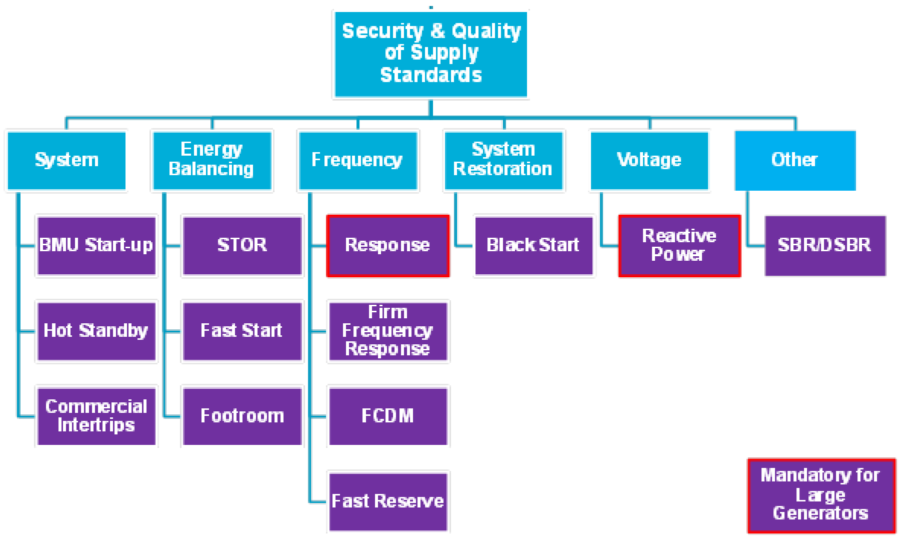
[3]See `https://www.nordpoolgroup.com/`

[4]See `https://www.theice.com/index`

In Britain, the National Grid carries the responsibility for keeping the grid in balance. The National Grid allows power to be traded in the wholesale market up to one hour before physical delivery (known as gate closure) when it takes over to remove any imbalances in the grid. This is done through the Balancing Mechanism. The Balancing Mechanism runs like a market where the system operator can procure balancing services from the balancing mechanism units (BMUs) — parties capable of increasing or decreasing generation or consumption in the grid.

Balancing services can be mandatory and non-mandatory and act on different time scales and for different purpose of maintaining the grid balance 3.2.

Figure 3.2: Categorisation of the balancing services offered by the National Grid. Source: (National Grid, 2016)

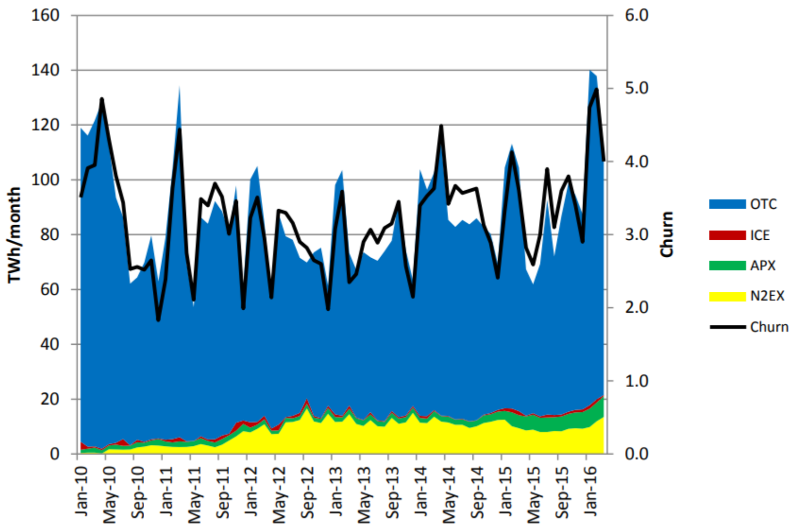


For example, firm frequency response service (FFR) gets activated within seconds of an event, whilst short term operating reserve (STOR) within minutes. Mandatory services, like reactive power provision and frequency response, are a prerequisite for large generators to be connected to the transmission grid (National Grid, 2016). This means that the generator must automatically react to the system frequency deviation in order to restore it. System management services, such as black start and hot standby, are there for the purpose of keeping enough generating capacity ready. The system operator (SO) passes the cost of balancing the grid on those parties which lead to system imbalance, whilst rewarding BMUs. Consequently, the wholesale price of electricity includes the cost of balancing the grid.

3.1.3 Electricity prices

Generally speaking, the closer to the time of physical delivery of power (i.e. the shorter the notice to generate) the higher are the prices for electricity generation and balancing services. For this reason, the majority of power (85%) is contracted for delivery in the over-the-counter market to fulfil the bulk of the known demand (or baseload) (Ofgem, 2016a). The remaining 15% of demand is traded on exchange as shown in Figure 3.3. Since OTC deals are agreed in private, it is difficult to obtain historical price information for the majority of electricity generated in the UK. However, the OTC market is strongly influenced by exchange prices for electricity, and so it is possible to use exchange prices as a proxy for OTC prices.

Figure 3.3: GB wholesale electricity trading volumes and churn, 2011 to 2016. Source: ICIS, APX, Nord Pool Spot, ICE, BEIS Energy Trends (Ofgem, 2016b)

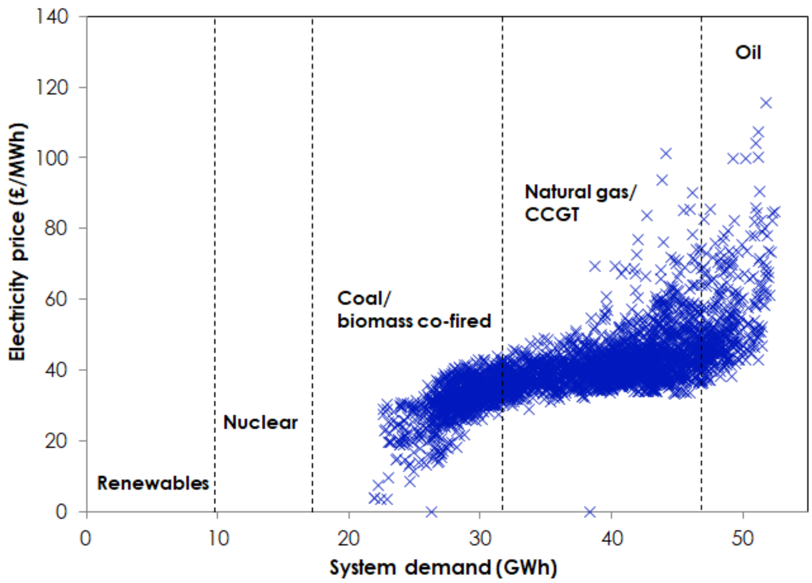


'Churn' is the number of times one unit of electricity is traded.

Figure E.1 demonstrates the historical relationship between system demand and the wholesale price for electricity.

It can be seen that as demand increases so does the price. This happens because cheaper units of electricity (those with lower short run marginal cost of generation) like renewables and nuclear get sold first leaving more flexible and expensive generation (like gas and oil) closer to the time of physical delivery. This results in what is known as the 'merit order stack', whereby generation units are arranged

Figure 3.4: Historical system prices and demand, Jan-Mar 2015. Source: (APX Group, 2015)



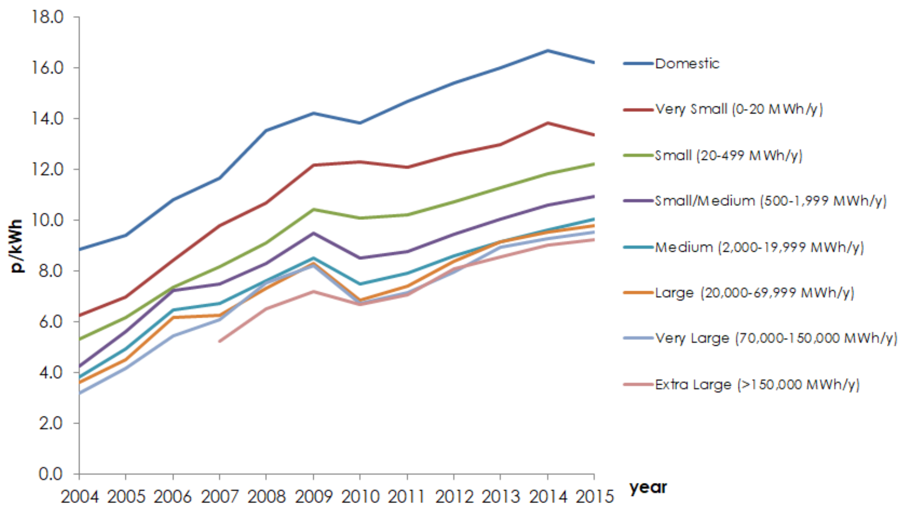
in the ascending order of price for electricity (which often reflects the short run marginal cost of production). The short run marginal cost of generation depends on the technical characteristic of the generation technology (its efficiency and variable operational and maintenance cost), the cost of fuel and the cost of greenhouse gases emitted from generating electricity. The rate at which a power generator can increase and decrease generation (ramp rate) determines whether it will run continuously or during peak times. For example, nuclear generators are expensive to cycle and so they tend to run continuously, whereas gas generators can cycle quickly, and are therefore used to meet peak demand. Hence, there can be situations when it is cheaper for the generator to run and to offset the extra supply by increasing demand rather than decreasing generation.

On the whole the process of electricity price formation is complicated as it involves different long-term and short-term markets, which can be skewed by speculative trading activity. The physical characteristics of the grid, grid balancing costs, prices for fuel carbon and external trading activity all affect the price for electricity. With increasing renewable capacity, this process is likely to become even more complicated. Since electricity generated from renewables comes at almost zero short run marginal cost it brings a structural change to the wholesale electricity market, which traditionally accommodates dispatchable generators.

3.1.4 Consumer electricity prices

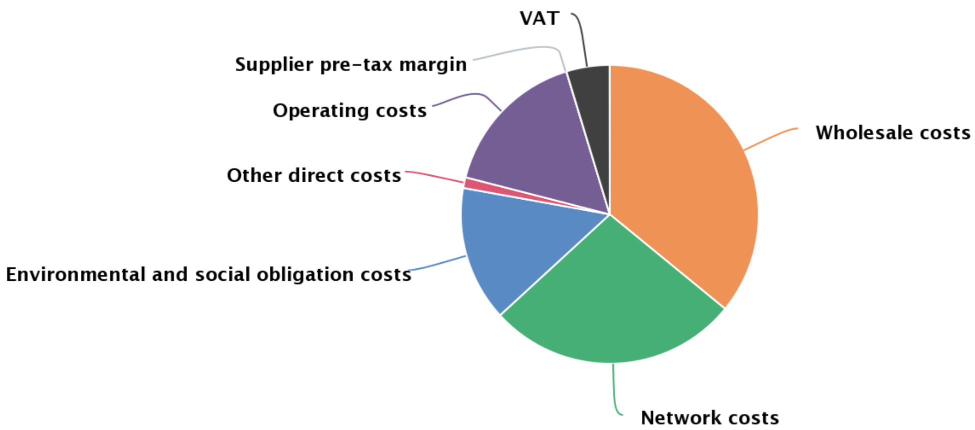
Whilst large consumers (large commercial and industrial) can purchase power directly from the wholesale market, smaller consumers (residential, small commercial) can only obtain electricity from an energy utility in the retail market. Hence, end-user prices for electricity differ depending on their size (Figure 3.5).

Figure 3.5: Historical annual consumer electricity prices by size, 2004-2015. Source: (Ofgem, 2016a)



Energy utilities purchase power on behalf of small consumers (like domestic or small commercial) in the wholesale market, whilst large commercial and industrial consumers can purchase electricity straight from the wholesale market. The costs incurred by the utility in the long-term, short-term and balancing markets all contribute to the wholesale price of electricity. The utility then uplifts the wholesale price to include the cost of using the transmission and distribution lines, as well as operational costs incurred by the company. Typically, the wholesale price of power contributes around a third to the retail price of electricity, whilst the network and the operational costs constitute 28% and 16.5% respectively (Figure 3.6). The remaining part of the retail price consists of environmental costs incurred by the utility (government programmes to save energy, reduce emissions and encourage take-up of renewable energy) and taxes (value added tax is paid on households' energy bills) (Ofgem, 2016a).

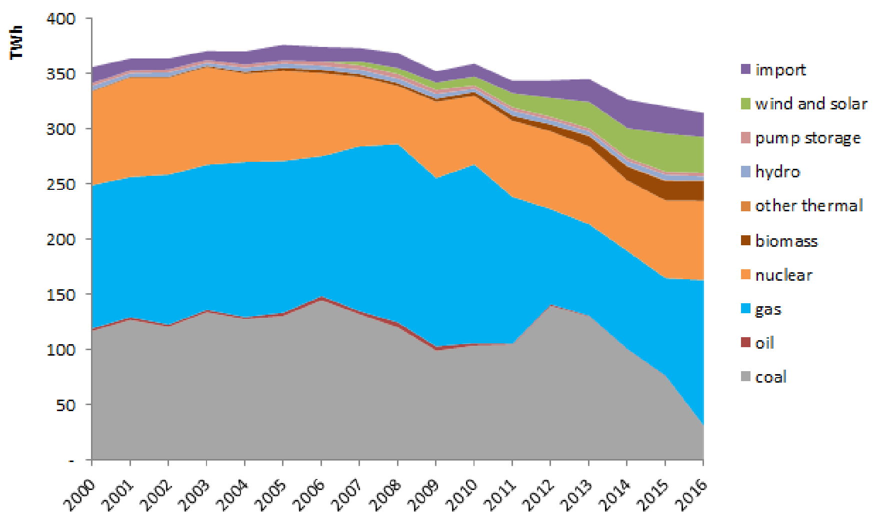
Figure 3.6: Breakdown of an electricity bill. Source: (Ofgem, 2017b)



3.1.5 Electricity system decentralisation

Traditionally, the British electricity grid operated in a centralised manner, whereby power generated by large generators was delivered to passive end-users. This set-up worked well, since electricity generated from burning fossil fuels can be controlled to match the electricity demanded by the system. However, in-line with the UK decarbonisation goals more and more renewable energy is being integrated into the grid (Figure 3.7).

Figure 3.7: UK fuel mix for generating electricity, 2000-2016. Source: (DECC, 2015)



Although some renewables are dispatchable (biomass and hydro), solar and wind generators suffer from unpredictability and variability of power generation. Moreover, a significant proportion of renewable generators (like embedded wind and solar) are smaller and geographically more dispersed. The demand side is also witnessing an increasing capacity of renewable generation, especially rooftop solar. This renders situations where end-users (especially in the residential sector) produce more than they consume, which necessitates them to export the surplus electricity back to the grid.

Heating and transportation electrification as well as lowering costs for storage technologies, are making end-users more flexible in consuming power. In order to engage end-users in utilising this flexibility, the UK government plans to equip every household with a smart meter by 2020 which would communicate the cost of electricity consumed in real time. This coupled with an increasing proliferation of commercially available smart home management system offered by companies like PassivSystems[5] and Nest[6] are making end-users more informed and more proactive in the way they consume electricity. This offers new business opportunities to energy utilities and aggregators. Companies like Tempus Energy, Ecotricity and Good Energy are moving towards a more flexible approach rewarding consumers who respond to dynamic tariffs therefore consuming more of renewable generation (Ecotricity, 2018; Good Energy, 2018).

The resulting system renders the perfect case study for investigating the impact of demand side management on the sustainability of the grid.

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[5] https://www.passivsystems.com/

[6] Nest2017

3.2 Assumptions

In order to build the model, the real system is simplified by making the following assumptions:

- The electricity network is modelled as a 'copper plate' (also known as 'single-node model'), meaning that power can flow unconstrained from any generation site to any demand site - a popular approach in economic modelling (Medjroubi et al., 2017).

- Modelled consumer agents correspond to pools of real-life consumers of the same type rather than individual entities. For example, all residential households with solar PV technology are modelled as one consumer agent. This assumption is deemed acceptable since consumers of the same type behave in the same manner.

- Speculative trading of electricity is omitted from the model, since it skews the real cost of generating electricity.

- Although the settlement in the UK is done on half-hourly basis, the temporal resolution of the model is set at 1 hour mainly due to the limitations in the temporal resolution of certain datasets. This assumption also makes the conversion between power and energy much simpler, whilst preserving the dynamic behaviour of the model.

- Wholesale electricity market is approximated as a single day-ahead market. This assumption is done in order to preserve the speed of the model, whilst still capturing the main mechanism of price formation.

- The balancing mechanism is approximated to a single generator rescheduling process done on the day which corresponds to real time electricity dispatch. Similarly to wholesale market assumption, this enables to preserve the speed of the model.

- Electricity import and exports are assumed to be constant throughout the year. This assumption spans from the fact electricity systems outside of Great Britain lie outside of the scope of this work.

- The cost of generating electricity is calculated based on the short-run costs including the ramping cost and ignoring the cost of investment. This assumption is justified by the fact that generation and storage capacities are taken as external input parameters.

- Uncertainty in predicting renewable supply is ignored. This is largely motivated by the fact that already today day-ahead wind forecasting errors amount to a few percent (depending on the country) and are even lower for solar. In the future, more data and better forecasting models are likely to reduce this error even further (Hodge et al., 2012).

- Uncertainty in predicting non-deferrable demand is ignored. This is justified by the fact that human activity like cooking, eating and working is unlikely to change significantly in the future. Hence, uncertainty in electricity demand is assumed to originate from operation of flexible resources like electric vehicles, storage, and electric heating.

- If the consumer has agreed to participate in demand response, he does not deviate from the demand profile after scheduling. This is because the social aspect of decision making by consumers lies outside of the scope of this work.

- Technical characteristics of power generators are assumed to be the same for the same type of power plants.

- District heating is not considered.

- Technical characteristics of power generators and consumer technologies (apart from non-deferrable demand) do not change throughout the simulation period.

- Seasonal environmental parameters (like external temperature, wind speed and solar irradiance) vary throughout the year but do not vary between years.

- In this work, DSM services offered by consumers are assumed to be free. This stems from the assumption that shifting flexible demand (from electric vehicles and/or electric heating) does not interfere with the quality of services offered to end-users. In addition to this, consumers are compensated either through a lower electricity tariffs achieved from a more optimal system demand profile (in the case of aggregator-led scheduling), or through expected cost reductions (when consumers schedule demand autonomously, in which case it is their own decision to alter demand). In reality, end-users can offer flexibility from shifting business-as-usual demand (e.g. cooking, watching TV, etc.) which would require compensation from the aggregator which calls for DSM services.

3.3 Agent-based modelling approach

The power sector represents a complex network of multiple stakeholders each with varying objectives and ways of interacting amongst each other and the environment. Traditional modelling approaches such as equilibrium modelling, optimisation and game theoretic models suffer from certain shortcomings when it comes to modelling real life socio-technical systems such as the power sector.

These include (Weidlich and Veit, 2008):

1. Modelling system actors as homogeneous agents, which is required to elegantly formulate the model;

2. Ignore agent learning characteristics;

3. Often assume perfect information available to all agents;

4. Assume continuous supply and demand functions.

The key feature of the proposed model is its capability to represent heterogeneous system stakeholders, which are able to adapt to the environment and learn the most favourable behaviour to them. Limitations discussed above make traditional methods inappropriate in recreating such behaviour.

Agent-based modelling (ABM) offers a way to decompose stakeholder interactions into simpler rules and presents practically and intuitively an effective way to model the proposed system. ABM uses autonomous decision-making entities called agents. In contrast with aggregated modelling, ABMs are guided by agent behaviour on the micro scale, which results in the emergence of system behaviour on the macro scale (Bonabeau, 2002). This is particularly important for modelling electricity system management, as the dynamics of demand and supply coordination very much depend on the behaviour of consumers which isn't linear. ABMs are flexible enabling to change the level of complexity of the model by adding or removing agents, rules and methods.

There isn't one set definition of what an agent is within the ABM community. Rather, an agent is defined as an entity that possesses the following characteristics:

Table 3.1: Agent characteristics. Source: (Wooldridge and Jennings, 1995)

Autonomy	Agents function independently and have control over their actions.
Social ability	Agents interact with other agents (or humans).
Reactivity	Agents are able to respond to the changes in their surrounding environment.
Pro-activeness	Agents' behaviour is guided by the rules and objectives assigned to them.
Learning	Agents can be equipped with learning algorithms which allows them to adjust their strategy.

Thus, depending on the domain of where the ABM is applied an agent may be an organism, human, business, institution, and any other entity that satisfies the above characteristics (Railsback and Grimm, 2011).

3.4 ESMA overview

In-line with the definition presented in Table 3.1, four types of agents are identified representing different actors in the British power system: consumers, aggregators, the system operator and the market (modelled as an agent in possession of different generation technologies) (Table 3.2). Agents have the capability to make decisions based on their observations of the environment, interact between each other and learn the best strategy.

Table 3.2: Agents considered in the simulation.

Agent	**Description**	**Objective**
Consumer	End-users from residential, commercial, industrial and transport sectors that purchase electricity from aggregators.	Fulfil own electricity demand at lowest cost.
Aggregator	Represents an entity which is able to pool consumers and buy electricity from a wholesale market.	Fulfil consumer electricity demand and maximise profit.
System Operator (SO)	Represents the system operator in Great Britain, i.e. National Grid.	Balance electricity supply with electricity demand.
Market	Represents the pool of electricity generators selling energy in the wholesale market	Schedule generators and calculate the wholesale electricity prices.

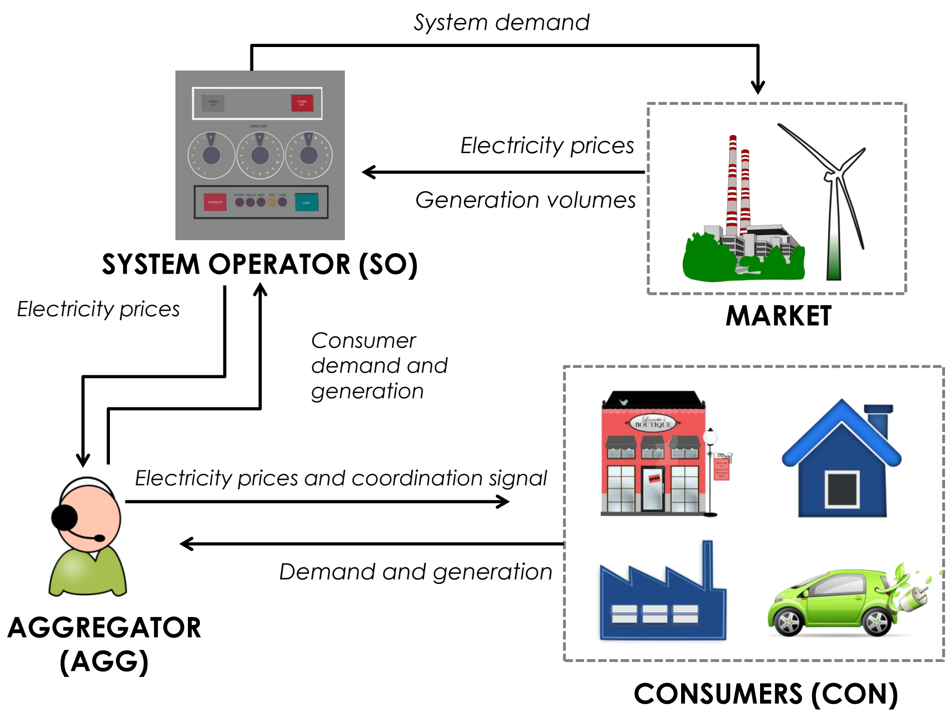
Figure 3.8 shows how the agents interact in the model in terms of the type of information they exchange. Consumers update aggregators with demand and generation profiles, who in exchange offer information on electricity prices and instruct consumers on how to shift demand during coordination. Aggregators update the system operator with consumer demand and generation profiles and receive information on the wholesale electricity prices. The SO communicates to the market system demand and generation data, based on which the market calculates generation volumes and electricity prices.

The following subsection explains the model in more detail going through each step of ESMA modelling.

3.4.1 ESMA algorithm

The proposed model runs on hourly basis with day-ahead planning horizon. Hence hourly and daily indices are introduced $t = 1,...,T$ and $d = 1,...,D$, s.t. $T = 24$, $D = 365$. The model is capable of performing long-term analysis which is achieved through updating model parameters like installed generation capacities, fuel prices

Figure 3.8: Graphical representation of model agent interaction in ESMA



and consumer technology numbers annually. The simulation year is tracked by index $y = 1,\ldots,Y$, where Y is the maximum number of simulated years. In our case $Y = 35$, however this value is constrained purely by data availability.

Figure 3.9 shows the overall model algorithm, whereby each block indicates different actions taken by agents throughout the simulation. For example, algorithm step R0 refers to the run initialisation, whilst C1 refers to consumers predicting renewable generation and daily residual demand profiles. The starred variables, e.g. $L^*(t,d), l^{c*}(t,d)$ correspond to predicted values and can therefore change throughout a simulation day, whereas non-starred variables, e.g. $R(t,d), r(t,d)$), cannot. Hence, renewable generation and non-deferrable electricity consumption is assumed to be deterministic in this model. The main source of uncertainty comes from consumers scheduling flexible demand resources, i.e. electric vehicles, heat pumps, and storage.

3.4.1.1 Model initialisation

Each simulation run starts with the model initialising in step R0 (shown in the purple box in Figure 3.9), which includes creating model agents and setting the scenario according to which the system will evolve (see Chapter 4). This step is performed only once during the simulation run. In the default setting (unless stated otherwise) the model creates 31 consumer agents (across all types and sectors as described in section 3.4.2.1), one aggregator, one system operator and one market agent.

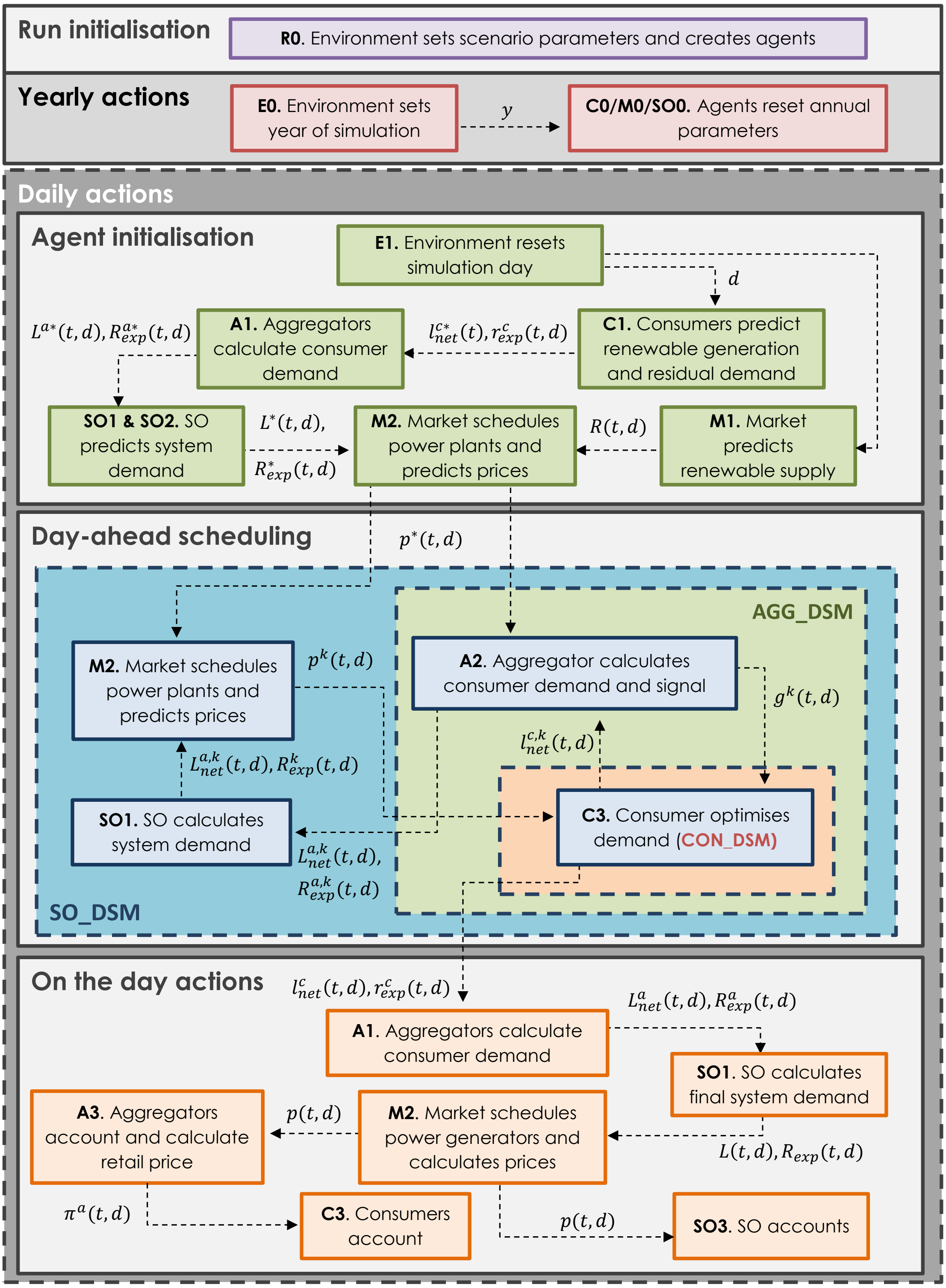
At the beginning of each year all model agents reset their parameters according to the chosen scenario (described in Chapter 4) and the year of simulation determined in step E0. The market agent resets the annual fuel prices, installed capacities and import levels, consumers update installed technology capacities (e.g. electric storage, heat pumps, electric vehicle numbers) (see Appendices C and D.1), and the system operator updates the grid losses (see Appendix C).

3.4.1.2 Daily actions

Daily actions surrounded by the grey box consist of three main blocks of activities: *agent initialisation*, *day-ahead scheduling* and *on the day actions*. During *initialisation* consumers set renewable generation $r^c(t,d)$ and residual demand $l^{c*}_{net}(t,d)$ in step C1. Consumers then pass the demand information onto aggregators which predict total consumer demand profiles $L^{a*}(t,d)$ in step A1. The SO receives information on consumer demand from the aggregators and makes a prediction of the system demand $L^*(t,d)$ in step SO1. Meanwhile, the market pre-schedules generators based on the predicted system demand $L^*(t,d)$ and renewables $R(t,d)$ to calculate predicted day-ahead electricity prices $p^*(t,d)$.

Day-ahead scheduling involves agents reacting to the predictions made in the initialisation stage by adjusting their demand. Different regimes for hierarchal DSM are considered, depending on the hierarchal layer which is responsible for instructing consumer demand scheduling (see Section 3.5). Central to each DSM regime is the demand response by consumers (CON_DSM) to aggregator signal, which corresponds to algorithm step C3 surrounded by the orange box. CON_DSM can be implemented more than once as indicated by the iteration index k.

Figure 3.9: Model algorithm.



The simplest and the most decentralised demand side response DSM regime, involves the consumers scheduling flexible demand based on the predicted real time price for electricity, in which case $g^k(t,d) = p^*(t,d)$. The algorithm is referred to as CON_CM, which corresponds to the consumer cost minimising behaviour. With CON_CM consumers schedule demand only once.

The next level of complexity involves an aggregator coordinating a pool of consumers (AGG_DSM in the green box), in which case the aggregator sends a signal $g^k(t,d)$ to consumers (algorithm step A2), who autonomously implement CON_DSM (algorithm step C3). Two types of AGG_DSM schemes are considered: demand flattening (AGG_DF) and cost minimising (AGG_CM). Whilst DF algorithm serves the grid through shaving peaks, the regime AGG_CM represents a more aggressive behaviour, whereby aggregators actively minimise the cost of power. AGG_DSM can involve many iterations until the system converges. In each iteration k consumers update aggregators with their demand profile $l^{c,k}$, whilst the aggregators recalculate the signal $g^k(t,d)$.

The most centralised hierarchal coordination regime (SO_DSM) surrounded by the blue box), involves the system operator negotiating demand with the aggregators, whilst constantly updating them with the new prices calculated by the market in algorithm step M3. Under SO_DSM the aggregators negotiate the demand profile with consumers in order to ensure convergence, and so blocks AGG_DSM and CON_DSM are active. Since the SO's objective is to reduce system cost only the cost minimising scheduling regime SO_CM is considered. Under SO_CM demand scheduling is performed during a number of iterations until convergence of the whole system is reached. Hence, algorithm steps C3, A1/A2, SO1 and M2 are implemented multiple times.

On the day activities include aggregators calculating the final consumer demand and generation profiles $L^a_{net}(t,d), R^a_{exp}(t,d)$ in algorithm step A1, followed by the SO aggregating final electricity demand and exports $L(t,d), R_{exp}(t,d)$ from utilities in algorithm step SO1. The market then reschedules electricity generators in algorithm step M2 based on the final demand profile $L(t,d)$ to calculate final wholesale prices $p(t,d)$. Once the wholesale prices are received, the SO calculates the cost of running the system in algorithm step SO2, aggregators calculate retail electricity prices and costs $\pi^a(t,d), C^a(d)$ in A3 and consumers calculate the costs based on retail prices. In some scenarios consumers are also allowed to switch aggregators based in the tariff $\pi^a(d)$ offered to them.

The following sections describe the actions of model agents in more detail with references to the algorithm in Figure 3.9.

3.4.2 Consumers

A set of N consumer agents is modelled $\mathscr{C} = \{c^1, ..., c^N\}$, where each $c \in \mathscr{C}$ represents a group of real life end-users of a specific type. Consumers' objective is to fulfil own electricity demand at minimum cost.

3.4.2.1 Creating consumers

Consumer type is determined by the combination of technologies available to the consumer. Five different technologies are considered: heat pumps (HP), resistance heating (RH), solar PV (PV), thermal energy storage (TES), and electrical storage (ES). Collectively these represent a set of technologies $\mathscr{T} = \{HP, RH, PV, TES, ES\}$[7], allowing to construct ten consumer types (Table 3.3).

Across the four economic sectors ESMA can build 31 different consumer agents, since the transport agent only allows one consumer type (i.e. with ES) as demonstrated in Table 3.4). In the default case, the model considers 31 consumer agents. As will be seen later, only when aggregator competition is modelled does the model build more than one consumer of each type. The numbers in each cell of Table 3.4 are an input of the modeller and indicate how many consumer agents of each type in each sector, n^{sec}_{type}, are created when the model is initialised (Algorithm step R0, Figure 3.9). For example, if $n^{dom}_{type1} = 2$ the model generates two agents, which represent two identical pools of residential households without any resources. The total number of consumer agents is calculated as $N = \sum_{type=1}^{10} \sum_{sec \in \mathscr{S}} n^{sec}_{type}$, where $\mathscr{S} = \{dom, com, ind, trans\}$ corresponds to a set of different consumer sectors.

[7]Electric vehicles (EVs) are represented as moving consumers with ES.

Table 3.3: Allocation of resources to consumer types.

Consumer type \ Technology	HP	RH	PV	TES	ES
1 (no resources)					
2 (with HP)	✓				
3 (with HP and TES)	✓			✓	
4 (with RH)		✓			
5 (with RH and TES)		✓		✓	
6 (with PV)			✓		
7 (with PV and ES)			✓		✓
8 (with ES)					✓
9 (with HP,PV,TES,ES)	✓		✓	✓	✓
10 (with RH,PV,TES,ES)		✓	✓	✓	✓

Key: HP - heat pump, RH - resistance heater, PV - solar photovoltaic, TES - thermal energy store, ES - electrical store.

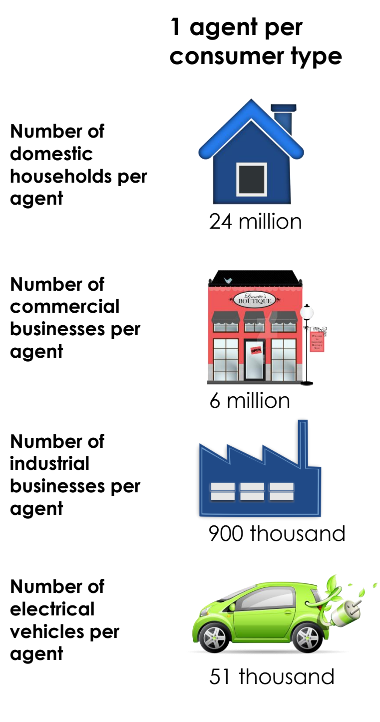
Table 3.4: Allocation of consumer agents to types.

Consumer type \ Sector	Domestic	Commercial	Industrial	Transport
1 (no resources)	n^{dom}_{type1}	n^{com}_{type1}	n^{ind}_{type1}	-
2 (with HP)	n^{dom}_{type2}	n^{com}_{type2}	n^{ind}_{type2}	-
3 (with HP and TES)	n^{dom}_{type3}	n^{com}_{type3}	n^{ind}_{type3}	-
4 (with RH)	n^{dom}_{type4}	n^{com}_{type4}	n^{ind}_{type4}	-
5 (with RH and TES)	n^{dom}_{type5}	n^{com}_{type5}	n^{ind}_{type5}	-
6 (with PV)	n^{dom}_{type6}	n^{com}_{type6}	n^{ind}_{type6}	-
7 (with PV and ES)	n^{dom}_{type7}	n^{com}_{type7}	n^{ind}_{type7}	-
8 (with ES)	n^{dom}_{type8}	n^{com}_{type8}	n^{ind}_{type8}	n^{trans}_{type8}
9 (with HP,PV,TES,ES)	n^{dom}_{type9}	n^{com}_{type9}	n^{ind}_{type9}	-
10 (with RH,PV,TES,ES)	n^{dom}_{type10}	n^{com}_{type10}	n^{ind}_{type10}	-

Key: HP - heat pump, RH - resistance heater, PV - solar photovoltaic, TES - thermal energy store, ES - electrical store.

Whereas the number of consumer agents may change, the total number of actual end-users they represent (or consumer multipliers, m^{sec}_{type}) stays the same. Figure 3.10 shows the conceptual representation of the idea. If 24 million residential households are modelled using one consumer agent, then that agent corresponds to the total number of residential households. However, if 24 million residential households are represented by three consumer agents, then each agent will correspond to 8 million residential households. This way of modelling preserves the total number of consumer resources, whilst keeping the model fast and flexible. There must be a minimum of one per each type enabling the analysis of the impact of DSM on all kinds of end-users. Of course in ESMA there are 31 different consumer groups depending on the type and consumer sector they represent. Therefore the allocation of end-users to consumer agents is slightly more complicated as it involves preserving the total number of technologies in the system.

Figure 3.10: An example of how real life end-users are represented by consumer agents.



Once the numbers in Table 3.4 have been set by the modeller they do not change during the simulation period. However, as the number of technologies change from year to year during the simulation period, consumer multipliers m_{type}^{sec} are adjusted to reflect this (see Appendix D.1). To give an example, if there is one residential consumer agent of type 8 ($n_{type8}^{dom} = 1$) representing 5000 real-life consumers ($m_{type8}^{dom} = 5000$) with 6kWh batteries each, the aggregate capacity of electrical store available to the consumer is calculated as:

$$6kWh \times m^{dom}_{type8} = 6kWh \times 5000 = 30MWh.$$

However, if there are two consumer agents of type 8 $n^{dom}_{type8} = 2$ representing 5000 residential consumers of type 8, then each domestic agent of type 8 will have storage capacity calculated as:

$$\frac{6kWh \times m^{dom}_{type8}}{2} = \frac{6kWh \times 5000}{2} = 15MWh.$$

Consumers update their resource capacities at the beginning of each year by multiplying individual technological capacities by the multipliers (algorithm step C0, Figure 3.9). In the next section when consumer technologies are discussed, technical characteristics refer to those of consumer agents rather than individual end-users.

3.4.2.2 Consumer resources

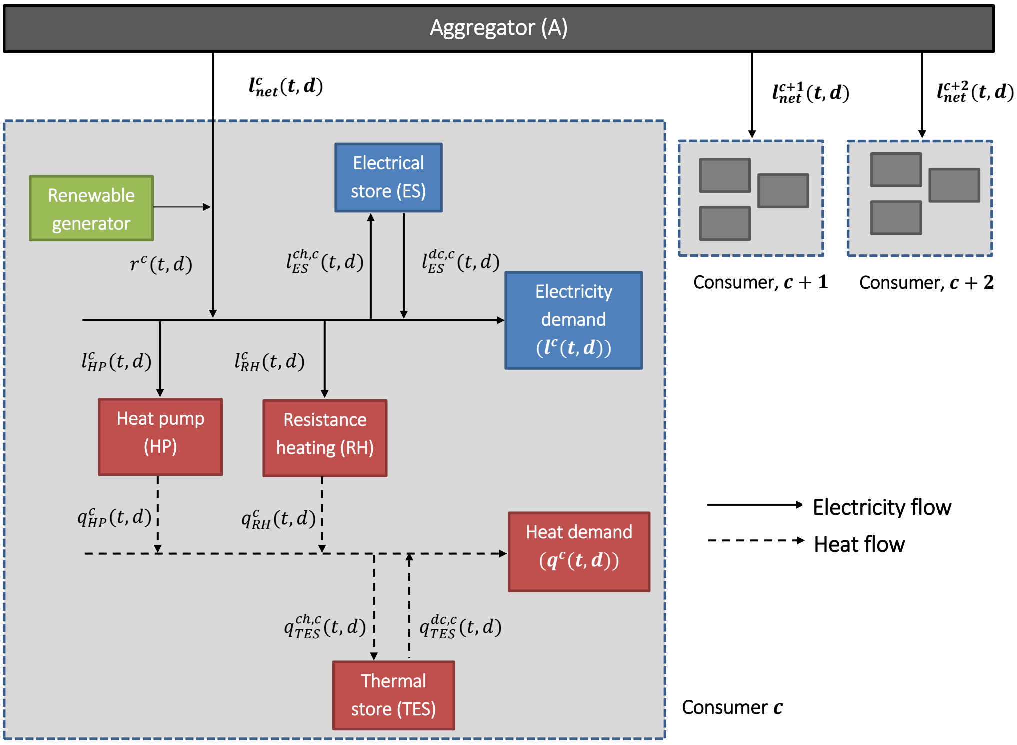
At the point when ESMA creates a consumer agent, it activates the appropriate technologies available to its type (Figure 3.11). Hence, a consumer of type 10 has access to all resources, whilst consumer of type 1 only has a heat pump.

All consumer types have a non-deferrable daily electricity profile $l^c(t,d)$, which represents electrical loads which cannot be shifted in time such as lighting or watching TV. Consumers in possession of electric heating such as a heat pump (HP) or a resistance heating (RH) also have a non-deferrable heat demand profile, $q^c(t,d)$. This is not to say that consumers with gas heating have no heat demand component, rather it is not considered as it does not contribute to the demand of electricity [8].

Consumers with access to ES and TES are able to shift demand, through charging and discharging electricity and heat. As will be seen in section 3.5, there are a number of potential mechanisms for scheduling demand serving consumer interests either directly or indirectly. The simplest one assumes cost minimisation or demand smoothing by consumers performed once, whilst more complicated algorithms use smart signalling by the aggregator to negotiate the optimum consumer demand curve over a number of iterations. Finally, consumers in possession of a

[8] See Appendix A.1 for an explanation of how non-deferrable demand profiles are obtained

Figure 3.11: General modelling set-up of the consumer agent



Note: consumer can have either a heat pump or a resistance heater and not both.

renewable generator (here represented by solar PV) can fulfil a proportion of their daily demand from own generated electricity $r^c(t,d)$[9].

Consumers calculate net electricity demand in step C1 (Figure 3.9) according to the following equation:

$$l_{net}^{c}(t,d) = l^{c}(t,d) + l_{ES}^{ch,c}(t,d) - l_{ES}^{dc,c}(t,d) + l_{HP}^{c}(t,d) + l_{RH}^{c}(t,d) - r^{c}(t,d), \quad (3.1)$$

Where for consumer c in hour t and day d,

$l^{c}(t,d)$ - non-deferrable non-thermal electricity demand [MWh],

$l_{ES}^{ch,c}(t,d)$ - electrical store charge [MWh],

$l_{ES}^{dc,c}(t,d)$ - electrical store discharge [MWh],

$l_{HP}^{c}(t,d)$ - electricity demanded by a heat pump [MWh],

$l_{RH}^{c}(t,d)$ - electricity demanded by a resistance heater [MWh], and

[9] See Appendix B.1 for an explanation on how these profiles are generated

$r^c(t,d)$ - electricity generated by renewable resources [MWh].

It is noted that in relation to the grid, transport consumers do not have non-deferrable demand $l^c(t,d)$, nor do they have any electric heating or renewable energy resources. Therefore for electric transportation, (3.1) is reduced to:

$$l^c_{net}(t,d) = l^{ch,c}_{ES}(t,d), \tag{3.2}$$

With respect to the vehicles themselves, transport consumers do have a non-deferrable demand, which is expressed by the discharge profile $l^{dc,d}_{ES}(t,d)$ and represents consumer constraints for utilising the vehicles[10].

3.4.2.3 Buying and exporting electricity

The net consumer demand, $l^c_{net}(t,d)$, calculated in (3.1) and (3.2) is what consumers obtain from the aggregator at retail price or tariff $\pi^a(t,d)$ calculated in Section 3.4.3.3. The total daily cost incurred by consumers (see Algorithm step C3, Figure 3.9) is calculated as follows:

$$z^c(d) = \sum_{t=1}^{T} l^c_{net}(t,d) \cdot \pi^a(t,d), \quad \forall c \in \mathscr{C}^a. \tag{3.3}$$

Later in the analysis the model considers the possibility of consumers switching aggregators based on the offered retail price $\pi^a(t,d)$. In this case consumers compare tariffs for electricity and choose one which is lowest.

In case the consumer generates more electricity than required, i.e. when

$$l^c_{net}(t,d) < 0,$$

that electricity is exported back into the grid. Consumer exports are calculated as:

$$l^c_{exp}(t,d) = -min(0, l^c_{net}(t,d)), \tag{3.4}$$

where the negative sign in (3.4) makes sure that the exports are positive from the perspective of the grid. In the default scenario, consumers get reimbursed for

[10]See Appendix C.2 for remaining technological constraints of consumer resources.

exported electricity at the wholesale price $p(t,d)$. As will be seen later the price for exported electricity affects how consumers schedule demand.

3.4.3 Aggregators

Aggregators represent stakeholders of the middle layer in the electricity system, which are able to pool consumers and supply them with electricity from the wholesale market. Aggregators can be vertically integrated and have the capability to sell power in the wholesale market or not, in which case they serve as coordinating entities for consumers. Regardless of the type, all aggregators have an objective to fulfil the demand for electricity of consumers that are contracted to them at minimal cost.

3.4.3.1 Creating aggregators

At the point of run initialisation (Algorithm step R0, Figure 3.9), ESMA creates a set of M aggregators, $\mathscr{A} = \{a^1,...,a^M\}$, where each aggregator represents a company which supplies a pool of consumer $\mathscr{C}^a$ with electricity. As a default setting, it is assumed that consumers of each type are equally split between aggregators. Hence, the number of consumer agents must be divisible by the number of aggregators as demonstrated in Figure 3.12. In the default setting only one aggregator is built by the model. However, when aggregator competition is explored (in the case of AGG_CM) and when consumers switch it is necessary to build more than one.

Aggregator daily activities include calculating total consumer demand and generation in algorithm step A1, scheduling consumers in step A2 and accounting at the end of the day in step A3 (Figure 3.9).

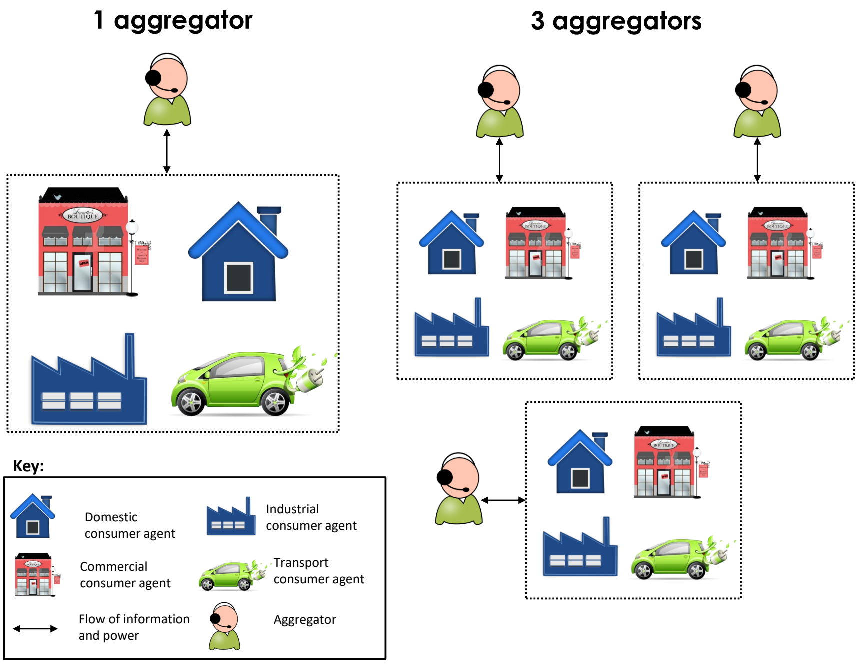
3.4.3.2 Calculating consumer demand and generation

At the beginning of the day $d \in [1,D]$ each aggregator $a \in \mathscr{A}$ calculates total consumer demand $L^a(t,d)$ by summing net demand across the pool of consumers it serves $\mathscr{C}^a$, i.e.

$$L^a(t,d) = \sum_{c \in \mathscr{C}^a} l^c_{net}(t,d), \quad \forall \quad a \in \mathscr{A}, t \in [1,T] \tag{3.5}$$

Algorithm step A1 calculated in (3.5) is actioned during daily initiation, scheduling and on-the-day actions. As the aggregator sums up net consumer de-

Figure 3.12: Example of consumer aggregation.



mand any exported electricity by consumers is shared across the whole pool of consumers served by aggregator a.

3.4.3.3 Aggregator accounting

At the end of the day, each aggregator a calculates the cost of power purchased during the day $C^a(d)$ (step A3, Figure 3.9):

$$C^a(d) = \sum_{t=1}^{T} L^a(t,d) \cdot p(t,d). \tag{3.6}$$

Finally, the aggregator calculates retail tariffs according to the following three approaches:

(1) The real-time price (RTP) - calculated as the wholesale price for electricity,

$$\pi^a(t,d) = p(t,d), \tag{3.7}$$

(2) Static price where the cost of electricity is averaged over the day,

$$\pi^a(t,d) = \frac{C^a(d)}{\sum_{t=1}^{T} L(d)}, \tag{3.8}$$

(3) Static price where the cost of electricity is averaged over a year,

$$\pi^a(t,d) = \frac{C^a(y)}{\sum_{t=1}^{T} L^a(y),} \tag{3.9}$$

Where,

$L^a(y) = \sum_{d=1}^{D} L^a(d)$ is the total electricity demand purchased by the aggregator during the year y, and $C^a(y) = \sum_{d=1}^{D} C^a(d)$ is the total cost of electricity incurred by the aggregator during the year y.

In reality retail prices are set somewhere in between dynamic and fixed tariffs. However, it is not certain how retail prices might be formed in the future, and so the three retail pricing regimes are left for exploration in this model.

As mentioned in Section 3.1.4, retail prices for electricity vary depending on the size of the consumer and include an uplift on the wholesale prices. Here the uplift is omitted because the focus of the work is to evaluate the intrinsic contribution of individual consumers to the cost of generating power at the transmission level, i.e. including the uplifts would include the operational costs of the aggregators.

3.4.4 System operator

The system operator (SO) represents the National Grid and carries the responsibility for balancing the system demand and supply. Hence, the SO tracks system electricity demand and supply in order to ensure a smooth flow. The SO stores the information of system demand daily, which allows it to make predictions for the day-ahead consumption. The SO communicates predicted demand to the market agent enabling it to schedule power generators (see Section 3.4.5).

At the beginning of the year when the SO initialises (Algorithm step SO0, Figure 3.9), it sets daily system losses $L_{loss}(t,d)$ and import values $L_{import}(t,d)$ according to the scenario and the year of simulation as described in Appendix C. It is assumed that the losses and imports are constant throughout the year and so the hourly values are calculated by dividing the annual values obtained from (National Grid, 2017a) by 8760 hours.

SO's daily activities include predicting demand, calculating actual system demand and accounting (steps SO1, SO2 and SO3, Figure 3.9).

3.4.4.1 SO calculating system demand

Once the aggregators have made a prediction on the day-ahead consumer demand, they pass this information to the system operator (SO), which aggregates it in algorithm step SO1, Figure 3.9:

$$L_{agg}(t,d) = \sum_{a \in \mathscr{A}} L^a(t,d), \quad \forall t \in [1,T], \tag{3.10}$$

The SO then makes a prediction for the day-ahead demand by weighing up predicted demand by the aggregators against yesterday's demand outturn:

$$L^*(t,d) = w \cdot (L_{agg}(t,d) + (1-w) \cdot L(t,d-1)), \tag{3.11}$$

where $L(t,d-1)$ is the system demand outturn in the previous day,
$L_{agg}(t,d)$ is the total electricity demand as predicted by the aggregators, and
$w \in [0,1]$ represents the weighing parameter to previous demand outturn.

The SO then send the predicted demand information to the market agent, which schedules electricity supply resources (see Section 3.4.5).

3.4.5 The Market

The electricity prices in the UK are set in a centralised market and depend on the system demand as well as the generation characteristics of the grid. A popular approach adopted by researchers to model the electricity market involves representing the historical demand and price relationship as a supply curve (Ramchurn et al., 2011; Zhang et al., 2014; Voice et al., 2011). However, this limits the model to sample-specific data making it inappropriate for simulating future electricity prices. Another state-of-the-art approach is to use economic dispatch modelling which schedules power plants based on the minimum cost of dispatch in order to fulfil system demand. However, detailed economic dispatch models such as (Walters and Sheble, 1993; Gaing, 2003; Hetzer et al., 2008; Chen and Chang, 1995) can take a very long time to solve and compromise the speed of the simulation. Instead, a simplified economic dispatch model is used based on (Van Den Bergh and Delarue, 2015), where power plants are aggregated by technology type and the start-up costs are omitted. An uplift to the resulting prices is then introduced in order to reflect the costs of using the network and balancing the grid using historical data taken from (Elexon, 2017a). This allows us to perform analysis into the future, whilst capturing stakeholder interactions on an hourly basis.

A note on model limitations. It is noted that technical characteristics (such as efficiency, ramping costs, operation and maintenance costs) of generators are fixed throughout the simulation period, meaning that if the efficiency of a generator was 60% in 2015 it will be the same in 2050. In addition to this, only the short term market is considered and the capital costs of generators are ignored. The limitations of the pricing model are acknowledged, however the reader is reminded that the focus of this work is to address the challenges associated with system control and cost allocation to consumers in the context of demand side management. Moreover, since generation capacities are taken as part of the scenarios, including investment costs is not necessary for reaching this objective.

3.4.5.1 Market resources

The market represents a pool of operational power generators in Great Britain grouped by technology type as demonstrated in Table 3.5. The model considers a set of thirteen technologies $\mathscr{G} = \{j^1, ..., j^G\}, s.t. G = 13$, which includes ten dispatchable types, alongside pumped storage (PS), solar and wind generators in accordance with the Future Energy Scenarios (FES) provided by (National Grid, 2017a).

Each power generation technology j is characterised by the price of fuel required to generate electricity (c^j_{fu}), efficiency(η^j), variable operation & maintenance cost (c^j_{op}), ramping cost (c^j_{ramp}), emissions factor (h^j_{CO2}) and capacity(cap^j). On creation of the market agent, ESMA generates a database which stores parameters of each technology type similarly to Table 3.5. Whereas technical generator parameters (i.e. operation and maintenance cost c^j_{op}, efficiency η^j, ramping cost c^j_{ramp} and carbon intensity factor h^j_{CO2} are fixed for the whole simulation period, fuel prices c^j_{fu} and capacities cap^j are updated annually in algorithm step M0 (Figure 3.9).

Table 3.5: Technical specifications of generation technologies and fuel prices in 2015. Sources: (UCL, 2016; Van Den Bergh and Delarue, 2015; IEA-ETSAP, 2010b,a,c; IAEA, 2014; Hawkes, 2010; Clark, 2013; Brander et al., 2011; ETI, 2016)

Technology type	Index (j)	Capacity (cap^j) [MW]	Fuel cost (c^j_{fu}) [£/MWh]	O&M cost (c^j_{op}) [£/MWh]	Ramping cost (c^j_{ramp}) [£/MWh]	Efficiency (η^j)	Emission factor (h^j_{CO2}) [t/MWh]
Biomass	1	2,229	28.6	2.3	1.3	0.34	0
Gas CCS	2	0.0	14.6	3.35	0.36	0.5	54
CHP	3	4,683	14.6	2.30	1.0	0.4	500
CCGT	4	24, 059	14.6	2.30	0.36	0.6	360
Coal	5	15,210	5.2	2.09	1.3	0.45	910
Hydro	6	1,333	0	0.2	-	0.45	0
Marine	7	8.4	0	0.2	-	0.2	0
Nuclear	8	7,278	0.04	2.13	80	0.32	0
Other therm †	9	1,270	23.7	0.88	1.3	0.45	610
Other RES ††	10	1,285	0	2.3	0.6	1	0
Pumped storage	11	2,744	0	-	0	0.8	0
Solar PV	12	0.0	0	0	-	1	0
Wind †††	13	13,049	0	0	-	1	0

† ‘other therm’ diesel, open-cycle gas turbines (OCGT), fuel oil, and onsite generation
††‘other RES’ includes geothermal CHP, waste CHP, anaerobic digestion CHP, waste CHP, landfill gas, sewage, and biogas CHP
† † † wind is considered both embedded and at the transmission level

The cost of generating electricity by technology j in the short run is referred to as the short run marginal cost of generation (c^j_{MC}), which is calculated according to the following formula:

$$c^j_{MC}(y) = c^j_{op}(y) + \frac{c^j_{fu}(y)}{\eta^j(y)} + h^j_{CO2}(y) \cdot p_{CO2}, \quad \forall j = j^1, ..., j^G, \tag{3.12}$$

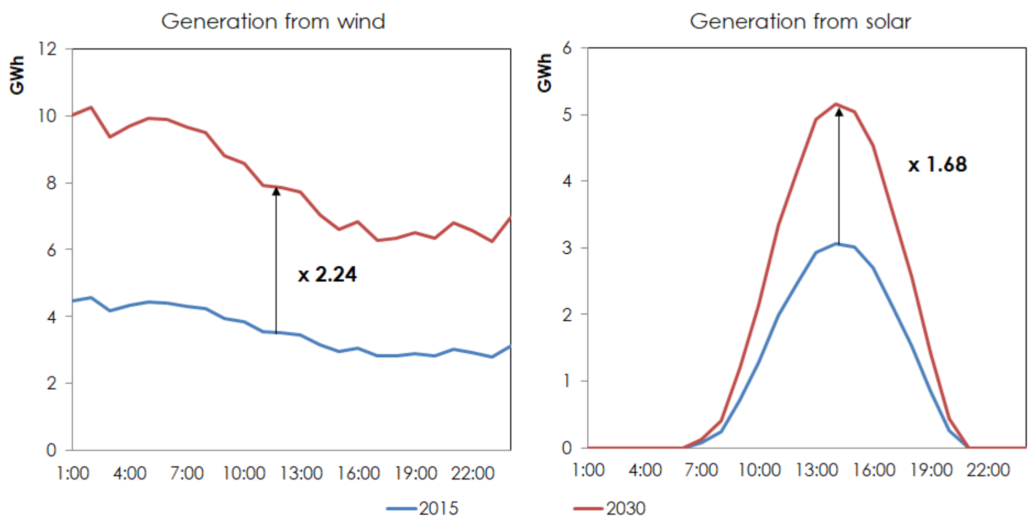
Where $p_{CO2} is the carbon price [/ton]$.

The short run marginal cost of generation is updated annually in-line with the fuel prices and does not change throughout the year hence the index y.

3.4.5.2 Predicting renewable generation

The market forecasts renewable generation (Algorithm step M1, Figure 3.9) by scaling historical generation profiles in accordance with the installed capacity of system level renewables [11]. Figure 3.13 demonstrate how the scaling for 2030 works for solar and wind on the 14th April.

Figure 3.13: Demonstration of wind and solar generation scaling from 2015 to 2030 on the 14th April. Source:(National Grid, 2017a).



If the total wind capacity increases from 13,049 MW in 2015 to 29,293 in 2030, then the generation output from wind in 2015 is multiplied by the relative capacity increase ratio, i.e. $\frac{29{,}293}{13{,}049} = 2.24$. Similarly, if solar capacity increases from 9,161 MW in 2015 to 15,417 MW in 2030, electricity output from transmission level solar in 2015 is multiplied by 1.68, calculated as $\frac{15{,}417}{9{,}161} = 1.68$. The profiles from wind and solar are then added together to represent transmission level renewable generation, $R(t,d)$.

3.4.5.3 Scheduling power generators

In order to model the electricity market a simplified least-cost dispatch model proposed by (Van Den Bergh and Delarue, 2015) is deployed. The market schedules

[11] see appendix C.1 for projected generation capacities.

generators twice throughout the day: during the 'day-ahead actions' based on the predicted system demand $L^{*}(t,d)$ calculated in (6.1) and during 'on the day actions' based on the actual demand outturn $L(t,d)$ calculated according to (3.10) (algorithm step M2, Figure 3.9). Here, the scheduling process is described using $L(t,d)$ to represents system demand but it is noted that the process is the same for pre-scheduling based on $L^{*}(t,d)$.

In order to validate the model against Future Energy Scenarios (FES) data provided by National Grid (2017a), system imports $L_{import}(t,d)$[12] and losses $L_{loss}(t,d)$ are included in the model. Since only the annual values for these variables are available (see Appendix C.1), a constant level of hourly imports and losses are assumed across the year by dividing the annual values by 8760 hours. Hence, transmission level generation and imports must cover consumer demand and losses, i.e.

$$L_{gen}(t,d)+L_{import}(t,d)=L(t,d)+L_{loss}(t,d), \tag{3.13}$$

Where $L_{gen}(t,d)=\sum_{j=1}^{G}q^{j}(t,d)$ is the total electricity generated across all technologies and $q^{j}(t,d)$ electricity generated by technology j in time t of day d.

The market schedules dispatchable generators in order to satisfy the balance equation (3.13) at least cost:

$$\min_{q^{j}(t,d)}\sum_{t=1}^{T}\sum_{j=1}^{G}(C_{SRAC}^{j}(t,d)+C_{dyn}^{j}(t,d)) \qquad \forall j\in\mathscr{G}. \tag{3.14}$$

Equation (3.14) consists of two cost component: the short run unavoidable cost ($C_{gen}^{j}(t,d)$) and the dynamic cost ($C_{ramp}^{j}(t,d)$) of generating electricity from technology j at time t in day d.

Term $C_{gen}^{j}(t,d)$ corresponds to the cost of running a generation technology j at short run marginal cost (or maximum efficiency) calculated as:

$$C_{SRAC}^{j}(t,d)=c_{MC}^{j}\cdot q^{j}(t,d), \quad \forall t\in[1,T], j\in[1,10], \tag{3.15}$$

where c_{MC}^{j} is the short run marginal cost of generation by technology j calculated according to (3.12) and $q^{j}(t,d)$ is the electricity output from technology j at

[12] Negative imports correspond to exports.

time t in day d.

The dynamic part $C^j_{dyn}(t,d)$ corresponds to the cost of cycling a power plant and hence includes the change in the generation level from one period to the next, i.e.

$$C^j_{dyn}(t,d) = c^j_{ramp} \cdot \delta^j_{ramp}, \quad \forall t \in [1,T], j \in [1,10], \tag{3.16}$$

where c^j_{ramp} has been set in market initiation step M0 and $\delta^j_{ramp} = |(q^j(t,d) - q^j(t-1,d))|$ is the absolute change in power generation from time $t-1$ to t of technology j.

Mathematically (3.14) is solved for $q^j(t,d)$ (power generated by dispatchable technologies), $L^{ch}_{PS}(t,d), L^{dc}_{PS}(t,d)$ (charging and discharging profiles of pumped storage) and $R_{curt}(t,d)$ (curtailed renewable profile) subject to the following operational constraints:

DC1: Total amount of generation from all resources must be equal to system demand $L(t,d)$ including losses:

$$\sum_{j=1}^{10} q^j(t,d) + L^{dc}_{PS}(t,d) + R_{used}(t,d) = L(t,d) + L^{ch}_{PS}(t,d) - L_{imports}(t,d) + L_{loss}(t,d), \tag{3.17}$$

where $R_{used}(t,d)$ is the amount of utilised renewable energy.

DC2: Pumped storage charge and discharge profiles are constrained by maximum and minimum power constraints:

$$0 \leq L^{ch}_{PS}(t,d) \leq L^{max}_{PS}, 0 \leq L^{dc}_{PS}(t,d) \leq L^{max}_{PS}, \tag{3.18}$$

DC3. The net amount of energy going into pumped storage is bound by its efficiency:

$$E^{net}_{PS}(t,d) = \eta_{PS} \cdot L^{ch}_{PS}(t,d) - L^{dc}_{PS}(t,d),$$

DC4. Total available energy stored by pumped storage $E_{PS}(t,d)$ is the sum of the available energy in the previous time period $t-1$ and the net charge in the current period t:

$$E_{PS}(t,d) = E_{PS}(t-1,d) + E^{net}_{PS}(t,d),$$

DC5. The amount of discharge $L^{dc}_{PS}(t,d)$ is limited by the available energy in the store:

$$L_{PS}^{dc}(t,d) \leq E_{PS}(t,d),$$

DC6. Total available energy stored by pumped storage $E_{ES}(t,d)$ must be within the capacity constraints:

$$E_{PS}^{min} \leq E_{PS}(t,d) \leq E_{PS}^{max},$$

DC7. At the end of the day the amount of energy stored by pumped storage must be the same as at the beginning:

$$E_{PS}(0,d) = E_{PS}(T,d),$$

DC8. : Total used $R_{used}(t,d)$ and curtailed renewable generation $R_{curt}(t,d)$ must add up to projected renewable generation $R(t,d)$ at the system level:

$$R_{used}(t,d) + R_{curt}(t,d) = R(t,d) \quad t \in [1,T]. \tag{3.19}$$

3.4.5.4 Calculating wholesale prices for electricity

The wholesale prices in the short run are calculated at the average cost per unit of energy demanded from the market, i.e.

$$p_{SR}(t,d) = \frac{\sum_{j=1}^{G}(C_{gen}^{j}(t,d) + C_{ramp}^{j}(t,d))}{L(t,d)}, \tag{3.20}$$

where $C_{SRAC}^{j}(t,d)$ and $C_{dyn}^{j}(t,d)$ are the predicted costs calculated according to (3.15) and (3.16).

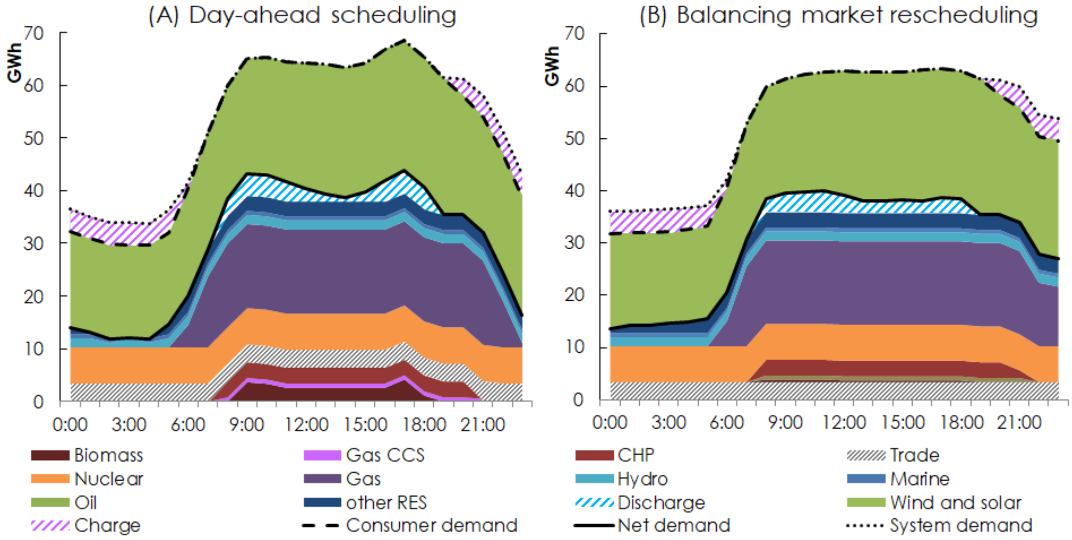
However, it is noted that $p_{SR}(t,d)$ is an underestimation of the real price of electricity as it does not include capital costs of the generators and the cost for the transmission and distribution network. In order to reflect the real cost of electricity, a demand dependent uplift $\varepsilon(L(t,d))$ is introduced, which takes into account additional costs of electricity generation such as the use of the network and the grid balancing costs (see Appendix E.1 for the methodology of modelling the uplift). The final wholesale electricity price is calculated as follows:

$$p(t,d) = p_{SR}(t,d) + \varepsilon(L(t,d)). \tag{3.21}$$

Figure 3.14 shows an example of implementing the scheduling methodology.

Figure 3.14 (A) shows day-ahead generation, whilst Figure 3.14 (B) shows rescheduled generation after the consumers responded to the signals from the aggregators under the AGG_DF DSM regime.

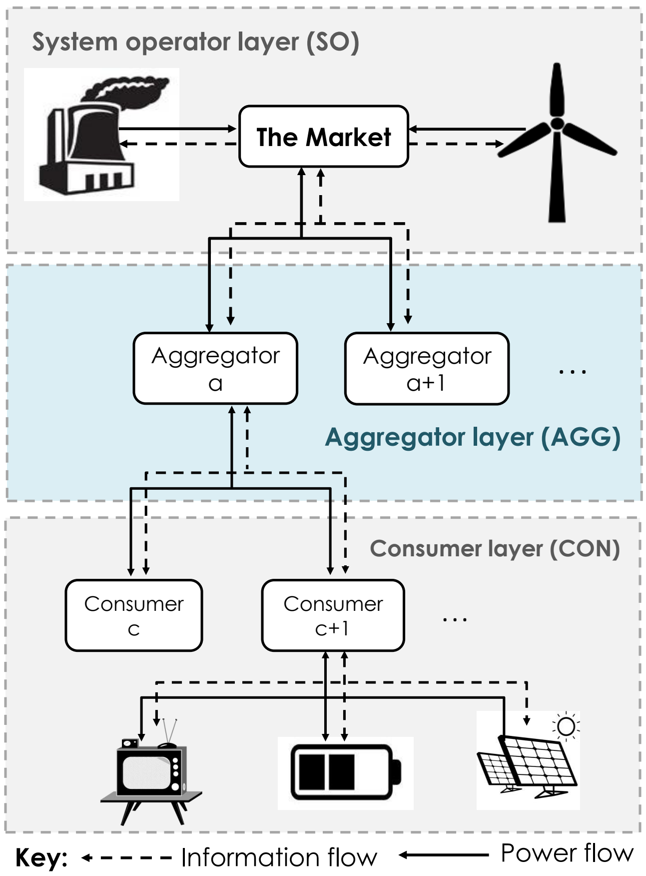
Figure 3.14: Example of market rescheduling under demand flattening coordination with 100 % participation in 2030 under AGG_DF algorithm (Two Degrees+).



3.5 Demand side scheduling

Three hierarchal layers of demand side coordination are considered: consumer, aggregator and the system operator (Figure 6.1), where the rational objective for performing demand side response by each of the stakeholder is to minimise the cost of power.

Figure 3.15: Agent hierarchy.



At the bottom level the model considers consumer-led demand response (CON_CM) with the aim of minimising individual consumer cost of power based on the projected real-time prices (RTP) received from the aggregator. Considering regime CON_CM is largely inspired by the popularity of using RTP as an incentive for end-users to consume electricity in a more efficient way. However this approach can lead to consumers herding towards the same periods of low prices leading to some unwanted consequences for the grid like increased demand peaks.

Aggregator-led coordination can overcome this problem, for which reason the model considers DSM regime AGG_DF based on the algorithm developed by (Gan et al., 2013). The algorithm receives it name due to the demand flattening (DF) effect it achieves. Yet, it is possible to imagine that aggregators may wish to make use of consumer flexibility in order to minimise the cost of power purchased from the wholesale market. In order to simulate such behaviour algorithm AGG_DF is slightly adapted into AGG_CM by allowing aggregators to communicate wholesale prices to consumers.

Finally, to simulate the most centralised yet hierarchal DSM regime algorithm SO_CM is developed, which is coordinated by the system operator whose objective is to minimise the total system cost. The algorithm works on a similar principle as AGG_DF but involves all stakeholders in the negotiation process of consumer demand profiles. Table 3.6 summarises all DSM regimes.

Table 3.6: Summary of demand side management (DSM) regimes.

Agent performing DSM	**Purpose**	**DSM name**
System operator	Cost minimisation	SO_CM
Aggregator	Cost minimisation	AGG_CM
Aggregator	Demand flattening	AGG_DF
Consumer	Cost minimisation	CON_CM

The following sections describe the algorithms for demand side coordination in relation to each of the stakeholders.

A note on the choice of decentralised coordination algorithm. After reviewing the literature on the different approaches for decentralised control it has been decided to opt for the iterative approach proposed by (Gan et al., 2013), whereby the aggregator slowly negotiates the demand profile with consumers over a number of iterations. This method constitutes a very flexible method for communicating the price information to consumers who have an equal chance to react. Other approaches include randomisation (Papadaskalopoulos and Strbac, 2016) and market-based coordination (Motto et al., 2002), however both of these methods introduce uneven opportunities for consumers to respond which makes the process of cost allocation more difficult. Finally heuristic methods (Vandael et al., 2011) and game theoretic approaches (Zugno et al., 2013) are not able to accommodate a more complex model of consumer behaviour with multiple flexible resources.

3.5.1 Consumer demand coordination algorithm (CON_CM)

The simplest and the most decentralised DSM regime constitutes a case when consumers cost minimise the projected cost of power based on the real time price received from the aggregator ($p^*(t,d)$). The algorithm is formulated as a mixed integer linear cost minimisation problem subject to constraints of consumer technologies (see Algorithm 1).

Algorithm 1: CON_CM: Consumer cost minimisation DSM algorithm.

Input : Aggregator a knows the predicted day-ahead prices for electricity $p^*(t,d)$. Consumers know day-ahead non-deferrable demand profiles, $l^c(t,d), q^c(t,d)$, renewable generation profile $r^c(t,d)$ and technical constraints of own resources.

Output: Consumer demand profiles:

$$l^c_{net}(t,d) \quad \forall c \in \mathscr{C}^a, \forall t \in [1,T]$$

1 Aggregator a sends consumers the predicted wholesale electricity prices:

$$p^*(t,d), \quad \forall t \in [1,T].$$

2 Each consumer $c \in \mathscr{C}^a$ solves the following optimisation problem:

$$\min_{l^c_{net}(t,d)} \sum_{t=1}^{T} l^c_{net}(t,d) \cdot p^*(t,d), \forall t \in [1,T],$$

subject to consumer technical constraints specified in Section 3.4.2.

3 Each consumer $c \in \mathscr{C}^a$ finalises net demand:

$$l^c_{net}(t,d) = l^c(t,d) + l^c_{HP}(t,d) + l^c_{RH}(t,d) + l^{c,ch}(t,d) - l^{c,dc}(t,d),$$

$$\forall t \in [1,T].$$

Figures 3.16-3.17 demonstrate how a pool of domestic consumers of type 9 (with HP,PV,TES and ES) utilise electrical and thermal storage with CON_CM in order to shift demand to periods of low electricity prices on a winter and a summer day.

Figure 3.16: Example of a daily demand profile by component for a pool of domestic consumers on a summer and winter day before coordination, Steady State (2030).

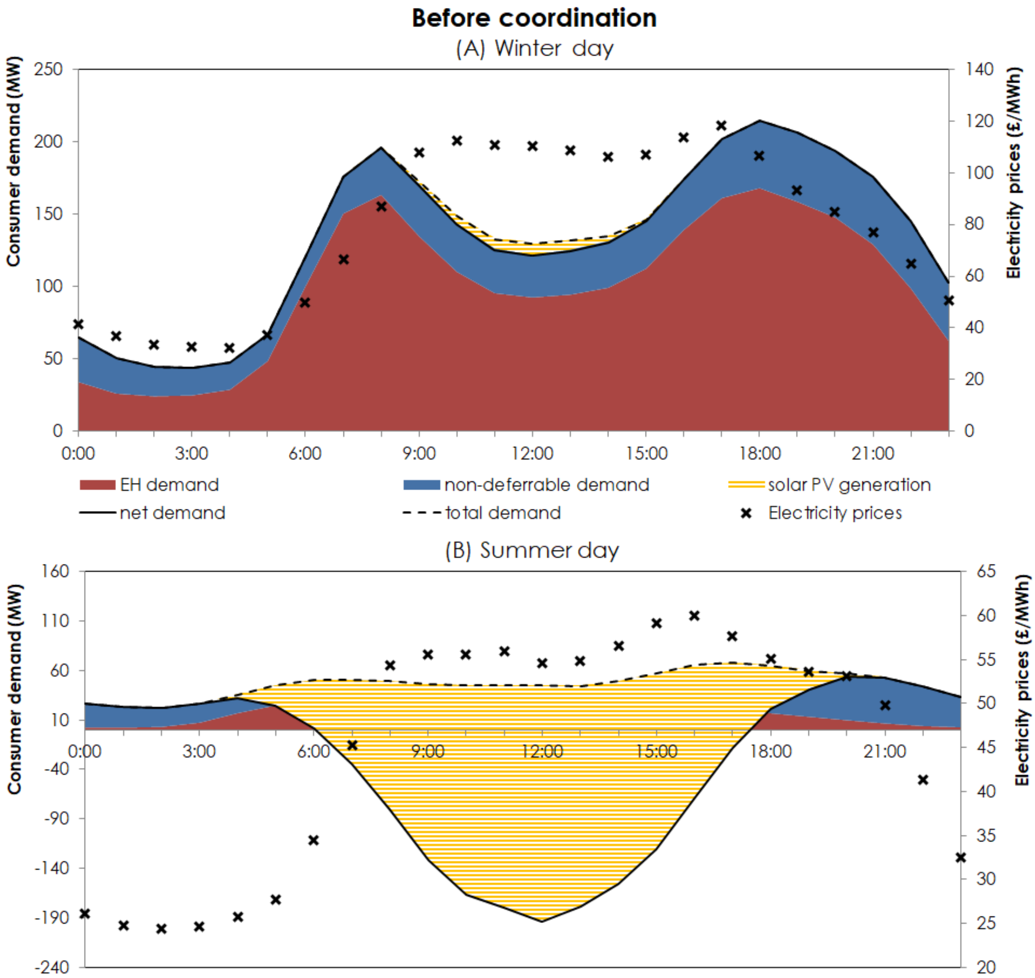
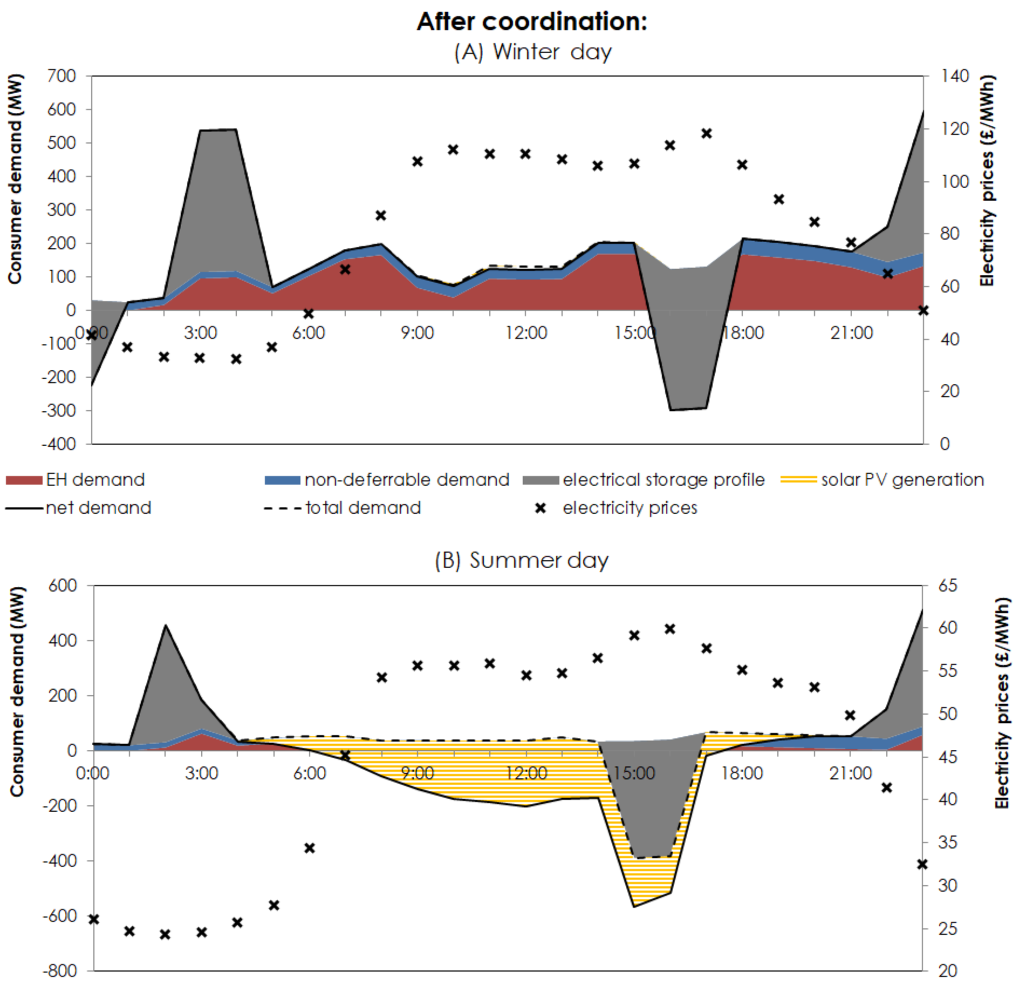


Figure 3.16 demonstrates consumer demand profiles on a winter and summer days in the business-as-usual (BAU) case before coordination. It is visible that in the winter consumers require a lot more heating (chart A), whereas in the summer solar generation profile is significantly higher (chart B). This translates into different flexibility and demand constraints for consumers.

Figure 3.17 demonstrates how consumer demand profiles change after scheduling with CON_CM. In both winter (chart A) and summer days (chart B), consumers charge their stores during the cheapest periods for electricity (00:00-03:00) and discharge them during the most expensive (09:00-12:00) and (15:00-18:00). In fact, consumer demand becomes negative during the most expensive time periods, which corresponds to end-users intending to export electricity. However, stricter constraints on heating demand and lack of solar generation energy means that in the winter the export peak is lower (300 MW) compared to summer (600 MW) when solar energy is abundant. On the other hand, demand peak is higher in the winter (550 MW) compared to the demand peak in the summer (400 MW). This is because in the summer consumers prioritise utilising storage for the purpose of absorbing solar generation, whereas in the winter storage is used to shift demand.

Figure 3.17: Example of a demand profile by component for a pool of domestic consumers on a summer and winter day after coordination with CON_CM with 100% participation, Steady State (2030).



Figures 3.18 and 3.19 show how consumer utilises storage to discharge energy during the most expensive periods on a winter day. Whilst non-deferrable heat and electricity demands stay the same, the overall electricity demand profile changes significantly. It is possible to see that thermal storage discharges during the morning and evening peaks, i.e. (09:00-12:00) and (15:00-18:00).

Figure 3.18: Electricity demand profile from electric heating for a pool of domestic consumers on a winter day before and after coordination with CON_CM with 100% participation, Steady State (2030).

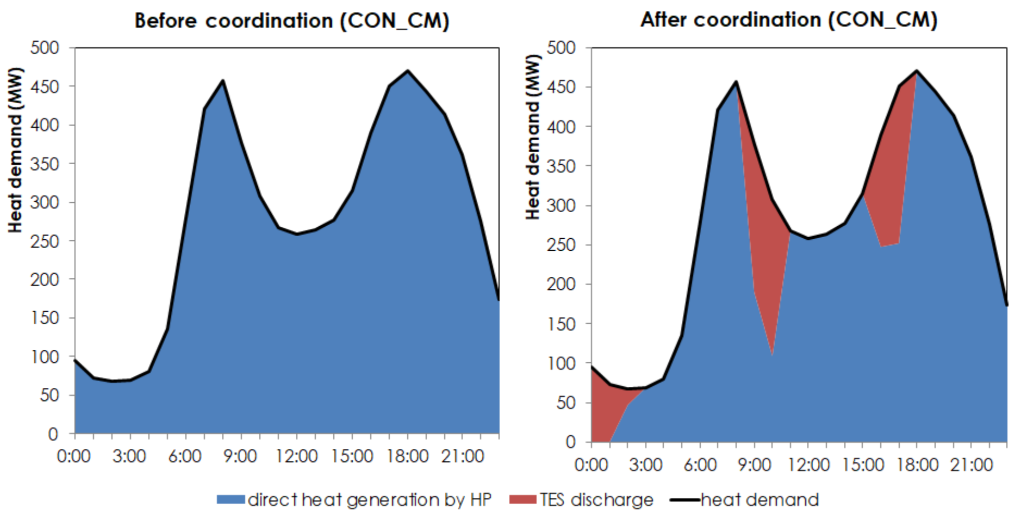
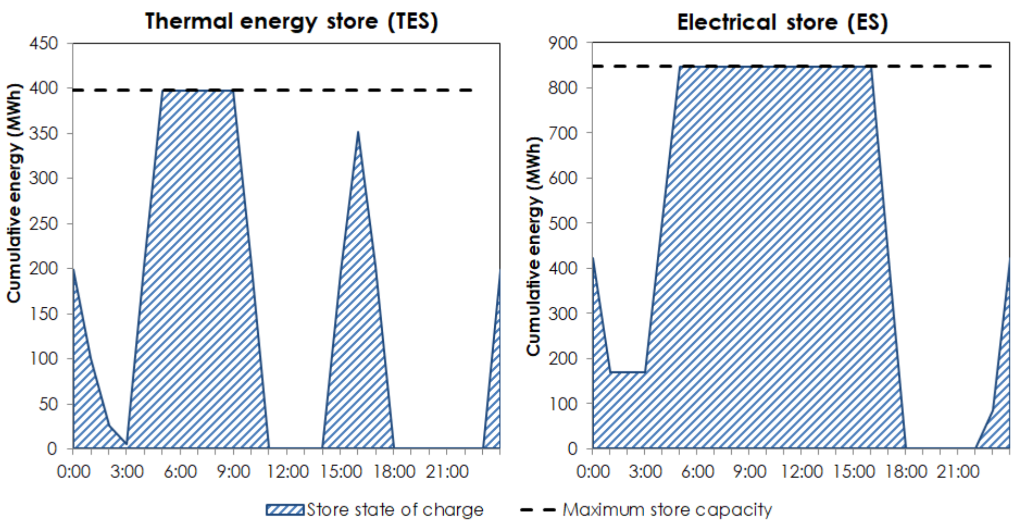


Figure 3.19: State of charge of TES and ES during coordination with CON_CM on a winter day with 100% DR participation, Steady State (2030).



3.5.2 Aggregator demand coordination algorithms

When it comes to aggregator-led coordination, a major concern is consumer privacy. Algorithm put forward by (Gan et al., 2013) allows the aggregator to indirectly schedule consumer demand over a number of iterations. The algorithm was initially developed for load smoothing with electric vehicles, however it has been adapted for scheduling consumers with any flexible load and renewable resources and named AGG_DF since it leads to aggregate demand flattening (see Algorithm 2). The algorithm works by supressing consumer cost minimising response to the aggregator signal through a parameter α (step 5 in Algorithm 2). As a result consumers are penalised for deviating from the previous demand profile which leads to a slow convergence of the whole pool of consumers to an equilibrium profile.

Algorithm convergence is measured in terms of the daily system cost since the objective of the algorithm is to reduce system cost. The convergence tolerance level has been set taking into account the speed and the accuracy of the algorithm (see Appendix E.2.1). In fact with a tolerance level of 0.005% the algorithm converges in 15 iteration the same as has been shown by the authors in the original work [13](Gan et al., 2013). Hence the maximum number of iterations are capped at 20 and the tolerance level is set at 0.005%,i.e. $K = 20, \varepsilon = 0.005\%$.

In order to model a more aggressive behaviour of a cost minimising aggregator, algorithm AGG_CM is developed by slightly changing AGG_DF (see Algorithm 3). In AGG_CM consumers receive the predicted prices for electricity rather than the average demand profile as in 2. Since the first term in consumer optimisation function now involves prices it was necessary to adjust the damping term α (originally set at 0.5 in algorithm AGG_DF). In fact it has been found that with the same tolerance level ($\varepsilon = 0.00005$) the algorithm performed best when α was set to 0 (see E.2.1), which rendered the same optimisation function for consumers as in CON_CM (Algorithm 1).

Figure 3.20 demonstrates how the two algorithms compare when it comes to scheduling consumer demand. In Algorithm AGG_CM the aggregator clearly tries

[13]Where the authors measure convergence as the difference between the optimal demand profile and the demand profile achieves after the final iteration

Algorithm 2: AGG_DF: Aggregator demand flattening DSM algorithm.

Input : Aggregator knows the number of consumers N_a it serves, predicted electricity prices $p^*(t,d)$ and aggregate consumer demand profile $L^a(t,d)$. Consumers know own day-ahead non-deferrable demand profiles, $l^c(t,d), q^c(t,d)$, renewable generation profiles $r^c(t,d)$ and technical constraints of own resources.

Output: Consumer demand profiles: $l^c_{net}(t,d) \quad \forall c \in \mathscr{C}^a, \forall t \in [1,T]$

Aggregator calculates initial cost of consumer power as:

$$C^0(d) = \sum_{t=1}^{T} L^a(t,d) \cdot p^*(t,d).$$

Aggregator a sets $k \leftarrow 0$ and $L^{a,0}(t,d) \leftarrow L^a(t,d)$

while $k < K$ **do**

Aggregator a calculates scheduling signal as the average of the projected demand profile across all consumers:

$$g^k(t) = \frac{1}{N^a} \cdot L^{a,k}(t,d), \quad \forall t \in [1,T].$$

Each consumer $c \in \mathscr{C}^a$ solves the following optimisation problem:

$$\min_{l^{c,k}_{net}(t,d)} \sum_{t=1}^{T} l^{c,k}_{net}(t,d) \cdot g^k(t) + \alpha \cdot (l^{c,k}_{net}(t,d) - l^{c,k-1}_{net}(t,d))^2 \quad \forall t \in [1,T],$$

subject to consumer technical constraints specified in Appendix C.2.

Aggregator a recalculates consumer demand

$$L^{a,k}(t,d) = \sum_{c \in \mathscr{C}^a} l^{c,k}_{net}(t,d), \quad \forall t \in [1,T].$$

Aggregator a calculates new cost:

$$C^k(d) = \sum_{t=1}^{T} L^{a,k}(t,d) \cdot p^*(t,d),$$

if

$$\left|\frac{C^k(d)}{C^{k-1}(d)} - 1\right| \leq \varepsilon$$

then

STOP.

else

Set $k \leftarrow k+1$;

end

end

Algorithm 3: AGG_CM: Aggregator cost minimising DSM algorithm.

Input : Aggregator knows predicted wholesale prices, $p^*(t,d)$, aggregate consumer demand profile $L^a(t,d)$, the total number of consumers it serves N_a, and the maximum number of iterations K. Consumers know day-ahead non-deferrable demand profiles, $l^c(t,d), q^c(t,d)$, renewable generation profiles $r^c(t,d)$ and technical constraints of own resources.

Output: Consumer demand profiles: $l^c_{net}(t,d) \quad \forall c \in \mathscr{C}^a, \forall t \in [1,T]$

Aggregator sets $k \leftarrow 0$ and consumers initialise demand as

$$l^{c,0}_{net}(t,d) = l^c(t,d) - r^c(t,d), \forall t \in [1,T], \quad \forall a \in \mathscr{C}.$$

Aggregator a initialises the cost of electricity as:

$$C^{a,0}(t,d) = \sum_{t=1}^{T} p^*(t,d) \cdot L^a(t,d).$$

Aggregator a sends consumers projected electricity prices $g^k(t) = p^*(t,d)$.

while $k \leq K$ **do**

Each consumer $c \in \mathscr{C}^a$ solves the following optimisation problem:

$$\min_{l^{c,k}_{net}(t,d)} \sum_{t=1}^{T} l^{c,k}_{net}(t,d) \cdot g^k(t) + \alpha \cdot (l^{c,k}_{net}(t,d) - l^{c,k-1}_{net}(t,d))^2 \quad \forall t \in [1,T],$$

subject to consumer technical constraints specified in Appendix C.2.

Aggregator a calculates new consumer demand as:

$$L^{a,k}(t,d) = \sum_{c \in \mathscr{C}^a} l^{c,k}_{net}(t,d), \forall t \in [1,T].$$

Aggregator a recalculates the predicted cost of power:

$$C^{a,k}(t,d) = \sum_{t=1}^{T} p^*(t,d) \cdot L^{a,k}(t,d).$$

if

$$\left|\frac{C^k(d)}{C^{k-1}(d)} - 1\right| \leq \varepsilon$$

then

STOP.

else

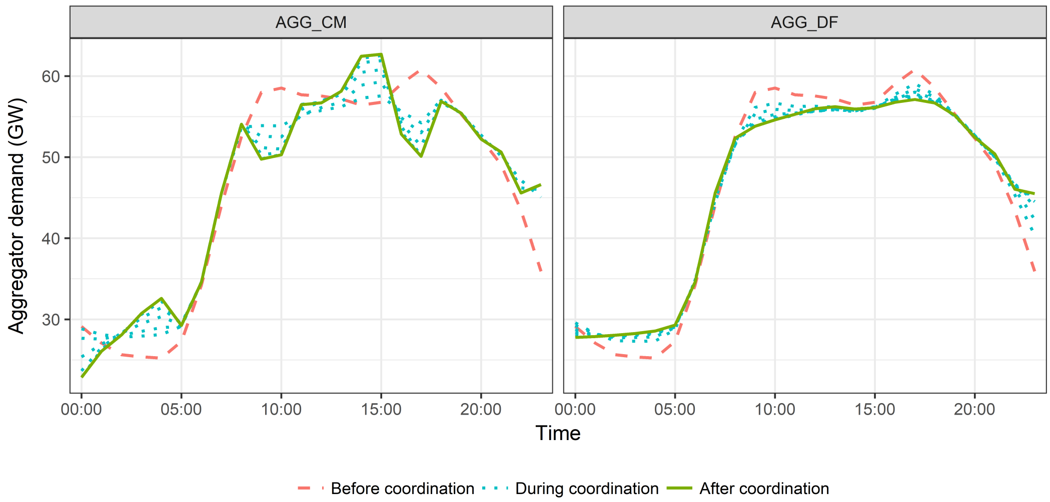
Set $k \leftarrow k+1$;

end

end

to maximise consumption at times of low electricity prices whilst in AGG_DF the result is a smoother demand curve.

Figure 3.20: Demonstration of algorithms AGG_DF and AGG_CM for 2050 in the Steady State scenario.



3.5.3 System operator demand coordination algorithm

Demand side scheduling by the system operator constitutes the most centralised demand side management regime where all the parties negotiate the day-ahead demand during a number of iterations (block SO_DSM in Figure 3.9). However, it still assumes indirect coordination since stakeholders send each other signals without directly controlling the devices. The objective of the algorithm is to minimise the system cost, hence it has been named SO_CM. In each iteration the SO acquires predicted price information from the market and communicates these to the aggregators, which in turn scheduling consumers. The consumers update aggregators with their new demand profiles and the aggregators pass this information back to the SO. The SO updates the market with the new predicted system demand and in return receives prices from the SO after the market has scheduled generators (Section 3.4.5.3). The SO calculates projected day-ahead costs and the process continues until the total cost has been minimised (based on the convergence tolerance set at 0.00005) (see Algorithm 4).

During the calibration procedure it has been found that the algorithm is sensitive to the damping parameter α which comes as a result of the changing level of the predicted electricity prices which counter balance the damping term in the consumer optimisation function. Therefore, it has been found that α needs to be adjusted daily depending on the average level of wholesale prices (see Appendix E.2.2). Similarly to Algorithm AGG_CM, algorithm SO_CM is calibrated for parameter α to ensure convergence.

Figure 3.21 shows SO_CM algorithm in action, whereby the projected system cost is reduced over a number of iterations (right). In fact the SO stops instructing aggregators to schedule after iteration 9 where the convergence tolerance is reached.

Algorithm 4: SO_CM: System operator cost minimising algorithm.

Input : The SO knows the predicted day-ahead system demand $L^*(t,d)$, prices $p^*(t,d)$, and the maximum number of iterations K. Each aggregator $a \in \mathscr{A}$ knows the set of consumers it serves $\mathscr{C}^a = \{a^1, ..., a^{N_a}\}$. Consumers know day-ahead non-deferrable demand profiles, $l^c(t,d), q^c(t,d)$, renewable generation profiles $r^c(t,d)$ and technical constraints of own resources.

Output: Consumer net demand profiles $l^c_{net}(t,d), \quad \forall t \in [1,T], \quad \forall c \in \mathscr{C}$.

SO sets $k \leftarrow 0$ and $p^k \leftarrow p^*(t,d)$ and calculates initial system cost

$$C^0_{SO}(d) = \sum_{t=1}^{T} p^*(t,d) \cdot L^*(t,d);$$

while $k < K$ **do**

The SO sends aggregators prices $p^k(t,d), \quad \forall t \in [1,T]$;

Each aggregator $a \in \mathscr{A}$ signals its consumer set $\mathscr{C}^a$ the predicted wholesale prices

$$g^k(t) = p^k(t,d), \quad \forall t \in [1,T];$$

Each consumer $c \in \mathscr{C}^a$ solves the following optimisation problem:

$$\min_{l^{c,k}_{net}(t,d)} \sum_{t=1}^{T} l^{c,k}_{net}(t,d) \cdot g(t) + \alpha \cdot (l^{c,k}_{net}(t,d) - l^{c,k-1}_{net}(t,d))^2 \quad \forall t \in [1,T],$$

subject to consumer technical constraints specified in Appendix C.2.

Each aggregator $a \in \mathscr{A}$ calculates new consumer demand profile

$$L^{a,k}_{net}(t,d) = \sum_{c \in \mathscr{C}^a} l^{c,k}_{net}(t,d), \quad \forall t \in [1,T]$$

and sends this information to the SO;

SO calculates new system demand profile

$$L^k(t,d) = \sum_{a \in \mathscr{A}} L^{a,k}_{net}(t,d), \quad \forall t \in [1,T]$$

and sends this information to the market;

The market calculates prices $p^k(t,d)$ according to (3.14);

The SO recalculates system cost as

$$C^k_{SO}(d) = \sum_{t=1}^{T} p^k(t,d) \cdot L^k(t,d), \quad \forall t \in [1,T].$$

if $|\frac{C^k_{SO}(t,d)}{C^{k-1}_{SO}(t,d)} - 1| <= \varepsilon$ **then**

STOP;

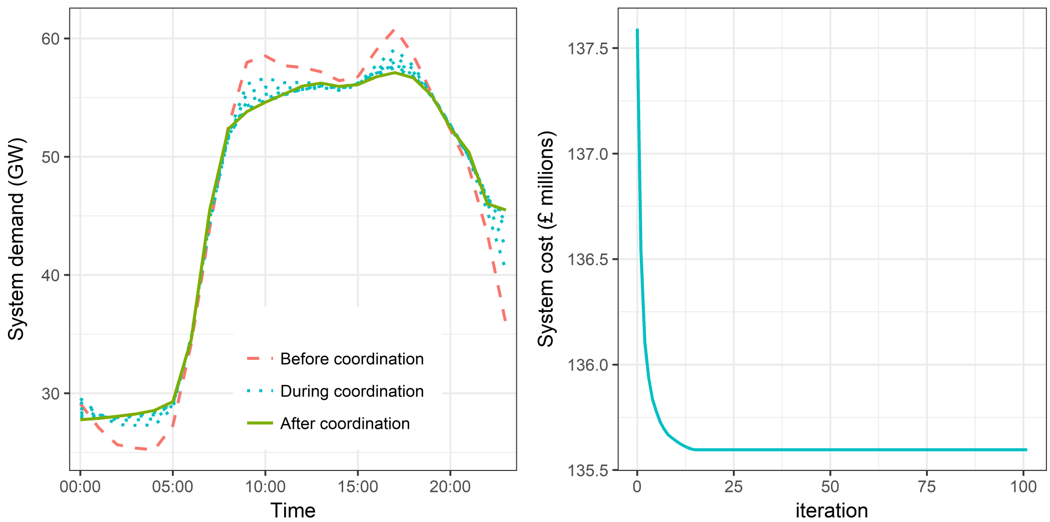
else

Set $k \leftarrow k+1$;

end

end

Figure 3.21: Example of SO_CM coordination algorithm performed for 2030 under Steady State scenario.



Chapter 4

Scenarios

The key feature of ESMA is its ability to model long-term impact of demand side management in the context of the British electricity grid. However, the model does not make decisions in terms of the generation mix, carbon prices, or the type of demand side management assumed in the system. Hence, when selecting simulation scenarios these parameters were considered as an external input in terms of two dimensions:

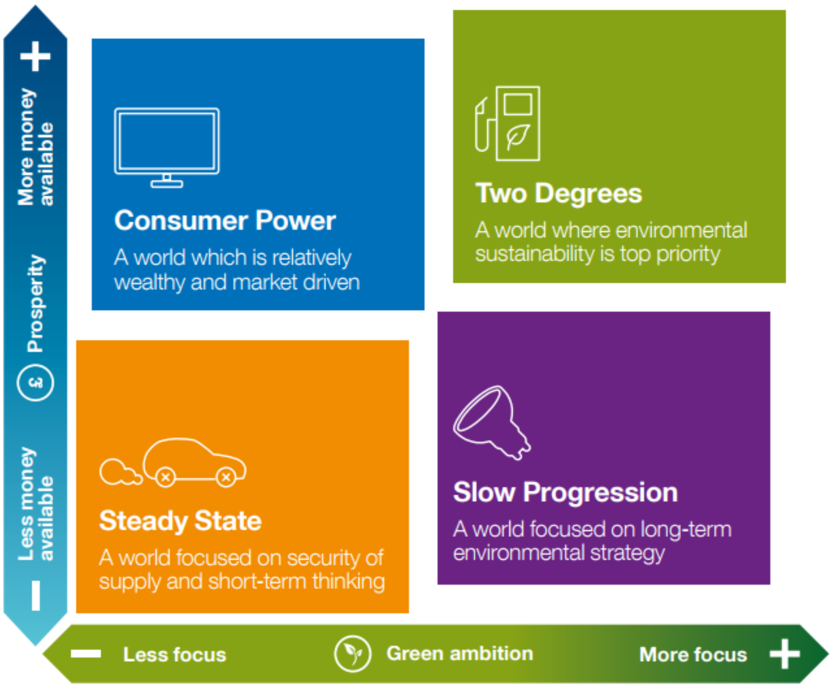
1. **National electricity system** - describing the physical evolution of the British electricity grid, i.e. consumer technologies, generation mix, fuel prices, number of consumers; and

2. **Demand side coordination regime** - describing stakeholder behaviour in coordinating the system demand, i.e. decentralised (coordinated by the consumer) or centralised (e.g. coordinated by the system operator).

The national scenarios are based on the Future Energy Scenarios (FES) provided by the (National Grid, 2017a), whereas demand side management regimes were constructed independently based on DSM regimes proposed in Section 3.5. This chapter is split accordingly and describes the process of selecting scenarios for each part.

4.1 National Scenarios

Figure 4.1: The British energy system scenario matrix. Source: (National Grid, 2017a).



The National Grid considers four cases for the evolution of the electricity system in Great Britain (GB): Steady State, Slow Progression, Two Degrees, and Consumer Power. Scenarios are classified according to two dimensions: prosperity and green ambition (Figure 4.1). The National Grid defines ‘prosperity’ as the amount of finances available in the economy, which could be directed towards government expenditure, investments in the private sector, and to consumers. ‘Green ambition’ reflects the level at which society and policies are prepared to direct finances towards increasing environmental sustainability.

Steady State and Consumer Power scenarios assume the lowest level of green ambition and see the least amount of renewable generation installed over the years. This is in contrast to Two Degrees and Slow Progression scenarios, which project the highest renewable capacity installed in the system in-line with the aspirations for a sustainable grid (Figure 4.2).

In terms of prosperity, Consumer Power and Two Degrees scenarios assume the highest level of wealth. Under the Two Degrees, finances are largely aimed towards reaching the green target, for which reason the system benefits from the highest capacity of transmission level renewables and storage. Under the Consumer Power, wealth is concentrated on the side of the consumers allowing them to acquire distributed renewables and storage (Figure 4.3). Both scenarios see a large number of electric vehicles (EVs). In contrast, Steady State and Slow Progression scenarios, assume a low level of prosperity and hence the proliferation of distributed consumer resources (such as electric vehicles, heat pumps and electric storage) is low (Figure 4.4).

Figure 4.2: Installed generation capacity by type. Source: (National Grid, 2017a).

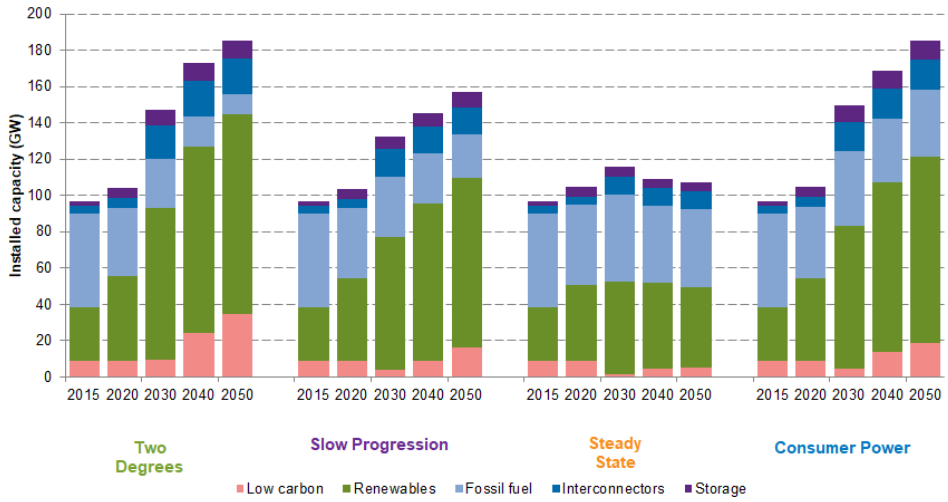


Figure 4.3: Installed electric storage capacity. Source: (National Grid, 2017a).

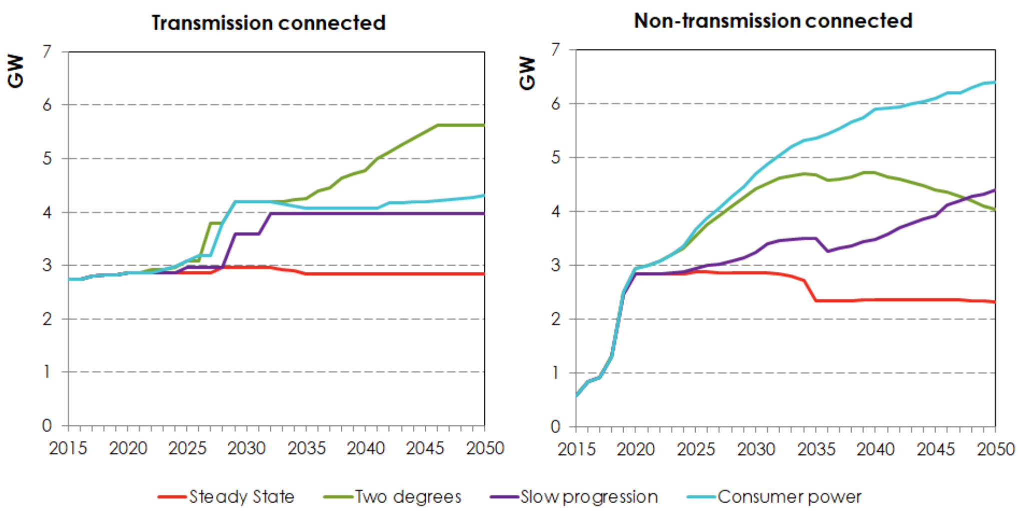
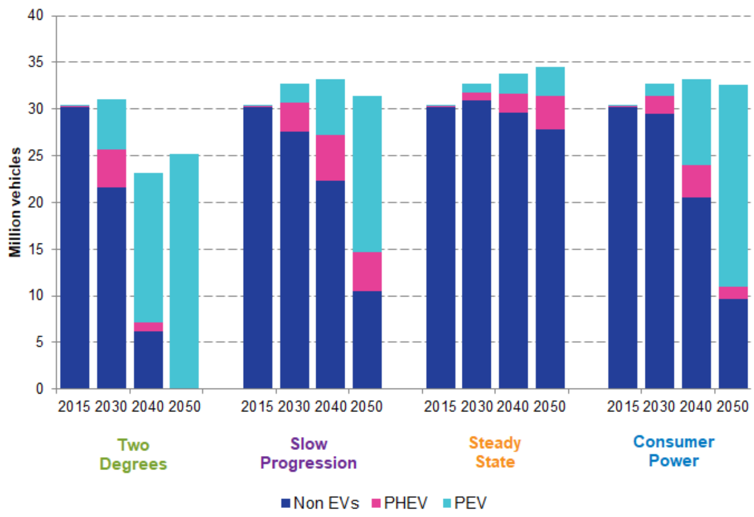


Figure 4.4: Number of electric vehicles on the road. Source: (National Grid, 2017a).

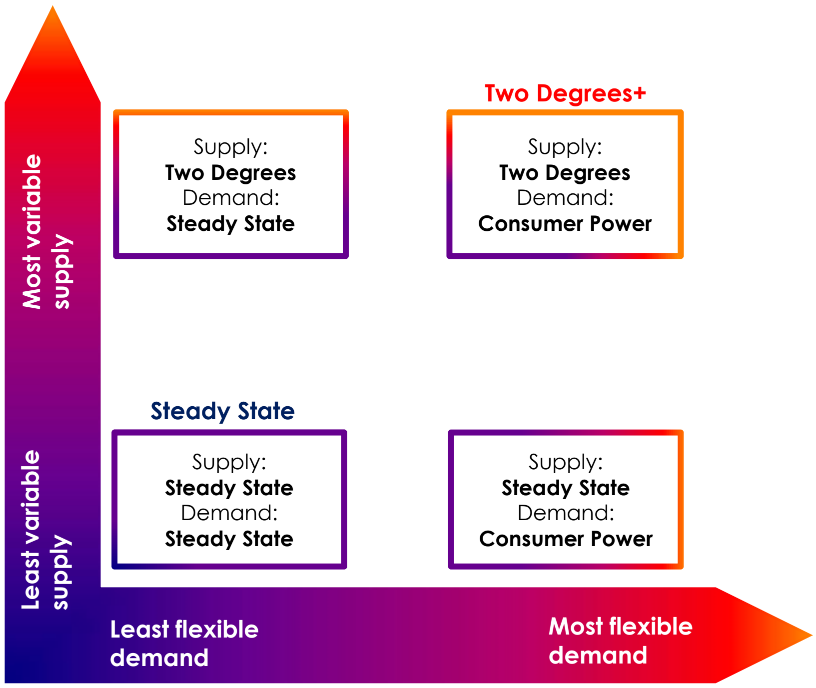


In order to narrow down the scenario scope, it has been decided to focus on the *boundary*, or *extreme* cases with respect to balancing the grid. These extremes originate from two sources: *variability* of electricity supply due to increased renewable generation capacity and *unpredictability* of demand due to the integration of consumer technologies such as distributed power generators and flexible storage. Extreme scenarios are considered with the objective of capturing the full spectrum for the future evolution of the British electricity grid.

The Future Energy Scenarios (FES) are redefined with respect to system *flexibility* and *variability* by considering the evolution of supply and demand sides separately (Figure 4.5). The y-axis characterises the system in terms of renewable generation capacity, whereas the x-axis specifies the amount of flexible demand resources (such as EVs and storage) assumed in the grid. This renders four boundary scenarios as demonstrated in the figure. For this reason, the case where the demand-side evolves according to Steady State and the supply-side according to the Two Degrees+ FES scenario appears in the top left corner, as it corresponds to an inflexible and variable system.

From the resulting four scenarios, the two most extreme cases are selected which correspond to the least variable and least flexible system (*Steady State*) and the most variable and most flexible system (*Two Degrees+*). *Steady State* scenario

Figure 4.5: Flexibility-variability matrix for scenario chose.



assumes a system, where demand is fulfilled mostly by fossil fuel, whilst nuclear generation and storage capacity is low. In contrast, the *Two Degrees+* scenario describes a system with a high renewable generation capacity (Two Degrees+ supply scenario) and a high level of demand flexibility (Consumer Power demand scenario). Together, Steady state and Two Degrees+ scenarios map out the full scope for the future evolution of the British electricity system. Consequently, the data being fed into the model is based on the values related to each scenario for supply and demand sides (see Appendix A).

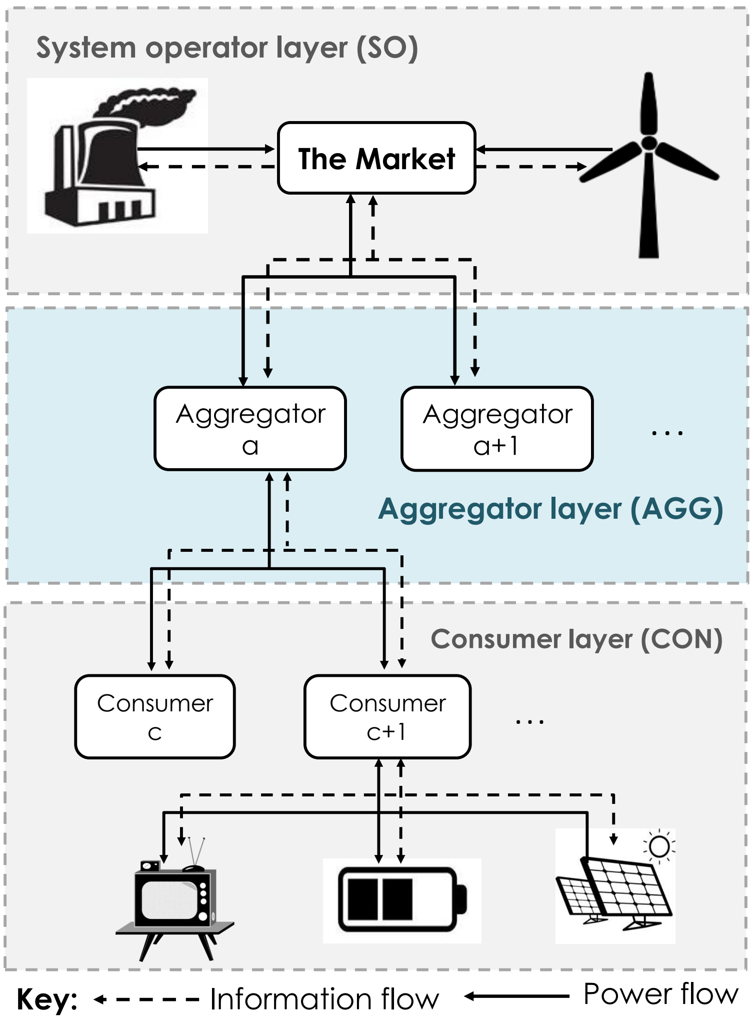
In order to conserve time when running the simulations three snapshot years are considered: 2015, 2030 and 2050. Year 2015 represents the base year against which the model is calibrated, 2050 as the year furthest into the future which ESMA can model (based on data availability), and 2030 as a midway point between the two, allowing to check the validity of the results and extrapolate the data in-between[1].

[1]Modelling every single year for the period 2015-2050 is possible with ESMA but, considering the time it takes to run each single year and the level of uncertainty regarding the future evolution of the system, the benefit of doing so is not justified.

4.2 Demand side response regimes

For demand side coordination, three hierarchal levels have been identified with the respect to the stakeholder which is responsible for scheduling. These range from totally distributed (performed by consumers), through semi-centralised (performed by the aggregators), to totally centralised when the System Operator oversees the whole process (see Figure 6.1).

Figure 4.6: Graphical representation of stakeholder levels and their interaction.



A note on terminology. It is important to mention that throughout the whole simulation, it is assumed that consumer resources are scheduled *automatically* via a smart demand controller system (subject to consumer participation in DSM).

To model different levels of DSM uptake, variables *conDR* and *aggDR* are introduced which determine the share of consumers and aggregators which participate in DSM. Both parameters lie between the values of 0% (no participation) and 100% (all participate). The impact of each DSM regime is measured under Steady State and Two Degrees+ scenarios in terms of system and consumer costs, greenhouse gas emissions (GHGs), and system demand peak.

4.2.1 Consumer DSM scenarios

At the consumer level three types of demand side management regimes are considered: CON_CM, CON_CM+, and CON_CM+(LEARN). Algorithm CON_CM represents the behaviour of a savvy consumer, who schedules demand in order to minimise the day-ahead cost of power based on the predicted real time price for electricity (see Section 3.5). Algorithm CON_CM+ evolves during the course of this PhD and represents an enhanced version of CON_CM, where consumer response is controlled via a centrally-set damping term α in order to avoid herding (see Section 6.3.1). In algorithm CON_CM+(LEARN) consumers can adapt to the market by learning consumer-specific damping term α^c themselves (see Section 6.3.2).

Regime CON_CM is considered in order to identify the conditions when consumer herding might become harmful to the system and regime CON_CM+ to demonstrate how controlling consumer response can help alleviate this problem. With CON_CM+(LEARN) we investigate whether complete consumer autonomy in demand scheduling is possible without compromising the security and stability of the grid. For each consumer DSM regime, the simulation is run for three snapshot years (2015,2030, and 2050) and two national scenarios: Steady State and Two Degrees+ (Table 4.1). For regime CON_CM, we investigate how consumer participation in DSM affects the system by considering three conDR settings (0%, 50% and 100%). Each DSM regimes is evaluated against the base case (when all stakeholders are passive) in terms of system and consumer costs, greenhouse gas emissions and system demand peak. Table 4.1 summarises the parameters for consumer DSM scenarios.

Table 4.1: Simulation scenarios for consumer DSM regimes.

DSM regime	National scenario	Year	conDR
Base case	Steady State,Two Degrees+	2015,2030,2050	0%
CON_CM	Steady State,Two Degrees+	2015,2030,2050	50,100%
CON_CM+	Steady State,Two Degrees+	2015,2030,2050	100%
CON_CM+(LEARN)	Steady State,Two Degrees+	2015,2030,2050	100%

Note: For regimes CON_CM+ and CON_CM+ 50% consumer participation level was not considered since comparison to other DSM regimes was done when *conDR* = 100% which corresponds to the most flexible scenario.

4.2.2 Aggregator DSM scenarios

At the aggregator level, two DSM regimes are considered: AGG_DF and AGG_CM (see Section 3.5 for details). In algorithm AGG_DF, the aggregator serves the grid by negotiating consumer demand for the purpose of smoothing system load. Hence by deploying AGG_DF, we explore the benefits of aggregator-led DSM. In algorithm AGG_CM, the aggregator actively minimises the cost of purchased power in the wholesale market, allowing to investigate the issues which may arise as a result of aggregators competing in the wholesale market.

In order to mimic the impact of DSM uptake by consumers and demonstrate the benefits of regime AGG_DF, parameter *conDR* is varied between 0%-100%. Similarly to consumer DSM scenarios, the simulation is carried out for the two national scenarios (Steady State and Two Degrees+) and three snapshot years (2015,2030,2050). The benefits of AGG_DF are evaluated against the base case (when all stakeholders are passive) in terms of system and consumer costs, GHG emissions and system demand peak (Table 4.2).

Table 4.2: Simulation scenarios under AGG_DF coordination regime.

DSM regime	National scenario	Year	conDR
Base case	Steady state,Two Degrees+	2015,2030,2050	0%
AGG_DF	Steady state,Two Degrees+	2015,2030,2050	50%,100%

It is demonstrated that aggregator herding is possible by deploying algorithm

AGG_CM. The damping parameter α (used in the algorithm to control consumer response to signalling) is varied in order to simulate different levels of aggregator cost minimising behaviour. When α is small, the aggregator instructs consumers to use more of their flexibility, whereas when α is high the aggregator penalises consumers for deviating too much from the previous schedule. The simulation is run for the period 2015-2050 in the Two Degrees+ scenario assuming that all aggregators cost minimise (Table 4.3).

Table 4.3: Simulation scenarios under AGG_CM (aggDR=100%).

DSM regime	National scenario	Year	Alpha setting (α)
AGG_CM	Two Degrees+	2015, 2030, 2050	0,0.005,0.05,0.5

For the last part, consumers are allowed to switch aggregators depending on the offered retail tariff. The rate of switching is varied from daily to quarterly in order to investigate how it might affect system prices and consumer costs. The analysis is performed when two aggregators with different resources compete for consumers in 2050 Two Degrees+ scenario (the most variable and flexible system) and compared to the base case (when all stakeholders are passive).

Table 4.4: Simulation scenarios under AGG_CM coordination regime with consumer switching.

DSM regime	National scenario	Year	Consumer switching rate	conDR
Base case	Two Degrees+	2050	none	0%
AGG_CM	Two Degrees+	2050	none,daily,monthly,quarterly	100%

4.2.3 System Operator coordination scenarios

The benefits of a centrally coordinated DSM are investigated by deploying algorithm SO_CM, which involves the System Operator communicating the cost of generating electricity directly from the market to the aggregators in real time (see section 3.5.3 for mathematical formulation). Similarly to the previous scenarios, the simulation is run for three snapshot years (2015,2030 and 2050) and two national scenarios (Steady State and Two Degrees+) assuming that all consumers and aggregators participate. The benefits SO_CM are evaluated against the base case (when all stakeholders are passive) in terms of system and consumer costs, GHG emissions and system demand peak (Table 4.5).

Table 4.5: Simulation scenarios under SO_CM coordination regime.

DSM regime	National scenario	Years	conDR	aggDR
Base case	Steady state,Two Degrees+	2015,2030,2050	0%	0%
SO_CM	Steady state,Two Degrees+	2015,2030,2050	100%	100%

Chapter 5

Model validation

The following chapter describes the process of validating ESMA. The purpose of doing so is two-fold: (1) to assess how good the model is at reproducing historical data and (2) to compare the output from ESMA against the Future Energy Scenarios developed by (National Grid, 2017a). The chapter is split accordingly.

In part one, output from ESMA for wholesale prices, demand and generation volumes is compared to historical data in 2015 (which is referred to as the *base year*). In part two, ESMA output is compared to the FES dataset for the period 2020-2050. The simulation is run for two key scenarios Steady State and Two Degrees+ and assessed in terms of reproducing prices, annual demand and generation volumes. Since FES data is used as an input to ESMA, comparing the two models serves as a check that the programmed interactions within ESMA are valid.

Validation is performed for the base case, without demand side management (DSM) for two boundary scenarios: Two Degrees+ and Steady State. This is because DSM is modelled explicitly in ESMA, therefore it is important to validate the case when all stakeholders are passive. Moreover, DSM can be implemented according to a multitude of scenarios and therefore it would be unreasonable to validate ESMA against only one or a few of them. It is noted here that both historical and FES datasets include a level of DSM, but it is not possible to detangle the system from the impact of DSM and so the data is taken assuming no DSM. Considering the level of uncertainty in modelling future consumer flexibility, it is deemed appropriate to make this assumption.

5.1 Historical data

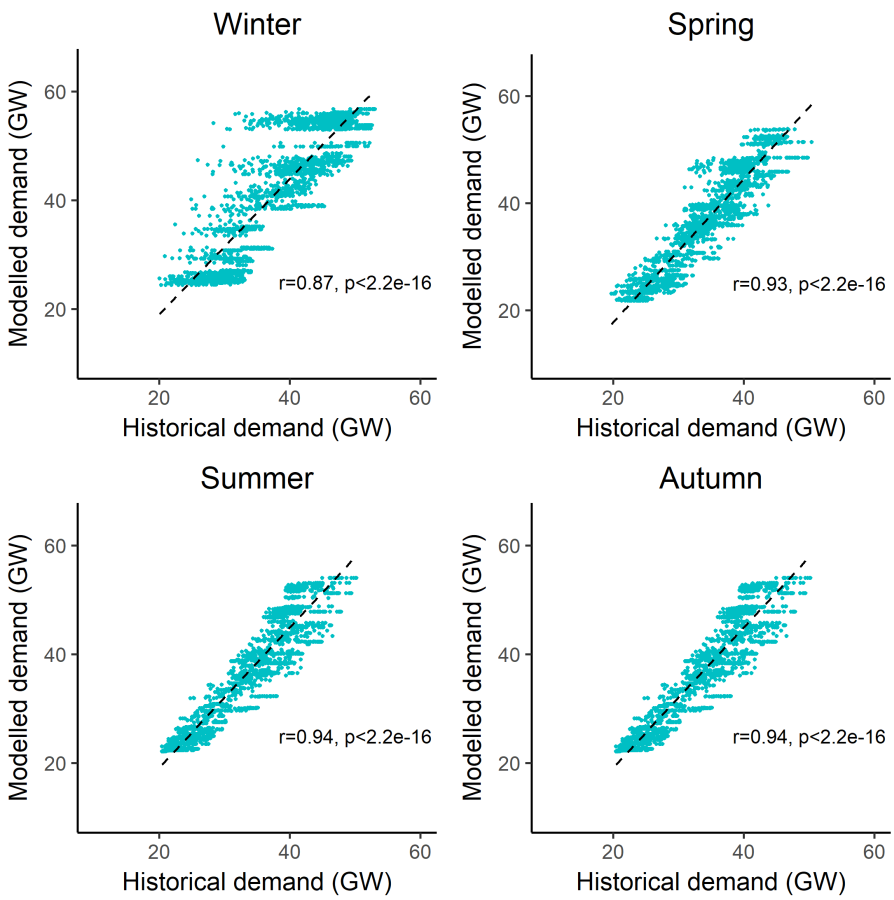
ESMA is validated against the *base year* (2015) by comparing generated system demand, prices and generation volumes to historical data.

A note on model assumptions. It is assumed that in the base year consumers do not participate in demand side management, however the system can utilise pumped storage in order to meet demand. This assumption allows us to obtain a reference point with regards to which consumers are considered as passive.

5.1.1 System demand

Figure 5.1 shows an hourly plot of historical and modelled system demand values split by season. The high correlation coefficient suggests that ESMA is effective at recreating the historical demand curve.

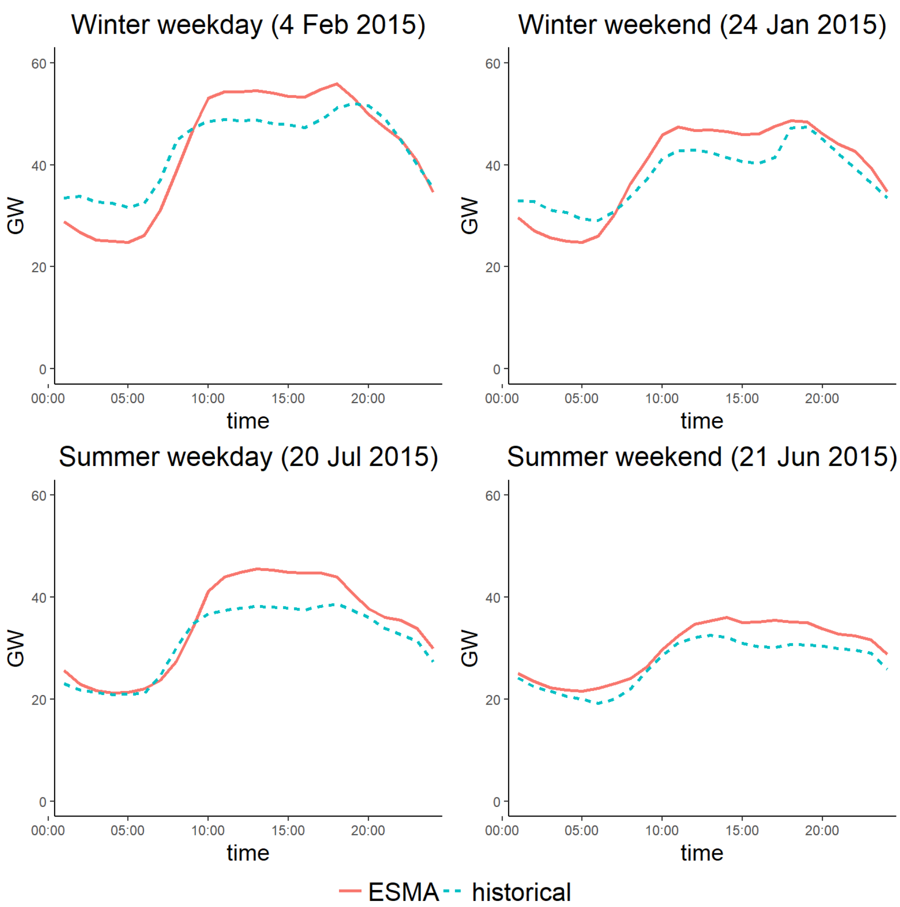
Figure 5.1: Comparison of hourly simulated and historical demand data by season in 2015. Source: ESMA and (National Grid, 2015c).



However, it is possible to see that the agreement between modelled and historical data is the worst for the winter season ($r = 0.87$). This can be explained by the fact that ESMA does not include Economy 7 consumers (representing 16% of total residential consumers), who benefit from a lower night tariff and in 2015 (BEIS, 2017a).

Looking at the hourly demand profiles confirms this hypothesis (Figure 5.2). From the figure it can be seen that in the winter historical demand is slightly higher at night which agrees with the behaviour of Economy 7 consumers who tend to operate storage at night. On the whole, the demand curve modelled by ESMA shows an acceptable level of agreement with historical data with an average correlations coefficient of 0.92 for 8760 hourly demand data points.

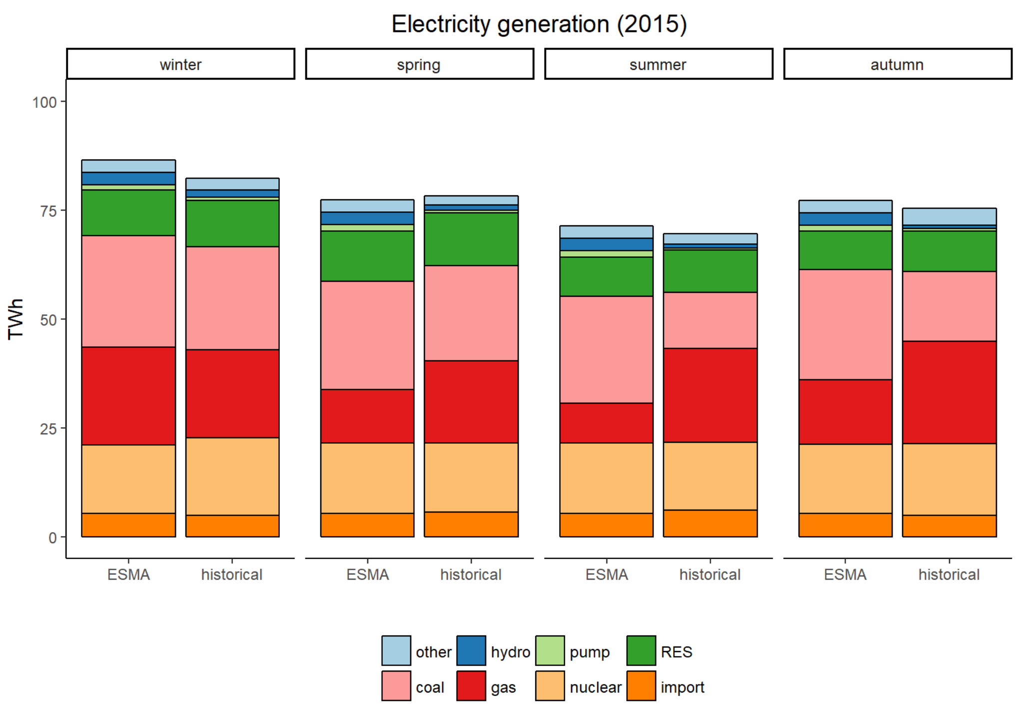
Figure 5.2: Examples of system demand curves for winter and summer weekdays and weekends in 2015. Source: ESMA and (BEIS, 2017a)



5.1.2 Electricity generation

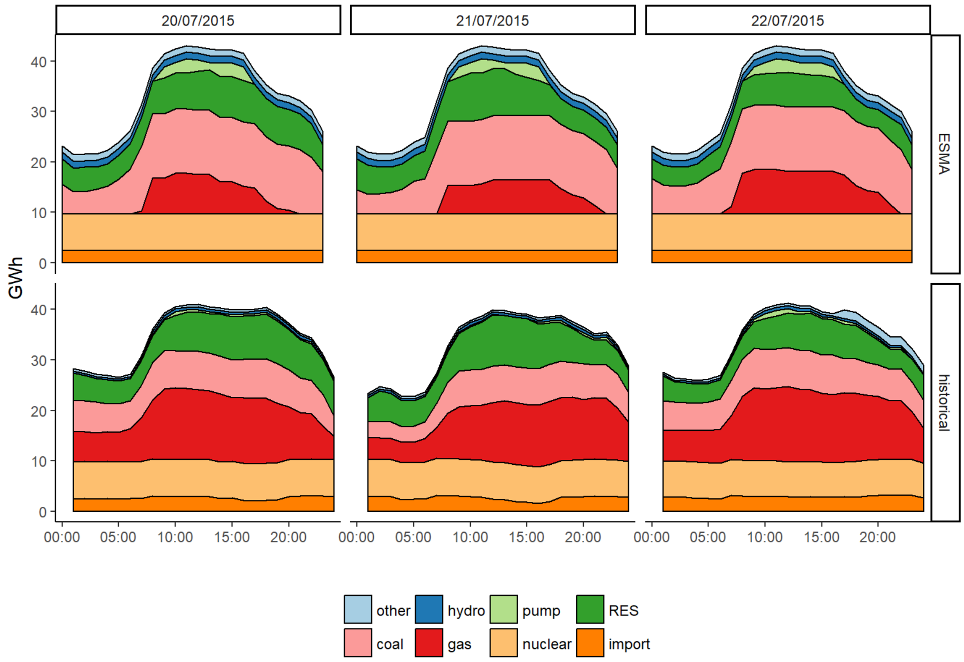
Figure 5.3 compares historical and modelled generation mix for four seasons in 2015. According to the figure, the use of nuclear, imports, renewables and pumped storage by ESMA is in good agreement with historical data. However, the model underestimates the use of gas, whilst overestimating the use of coal for summer and spring days in particular. This is because in ESMA the price for primary fuels is fixed across the year, whereas in reality it fluctuates throughout the day. By taking an average low price for coal in 2015, ESMA prioritises the use of coal-fuelled to gas-fuelled generation. In fact in 2015, the price for natural gas in the UK fell 26% during the year, which explains why according to historical data gas was used more in generating electricity (especially towards the second half of the year) (Ofgem, 2016b). It is also possible to note that compared to historical data, ESMA generates slightly more electricity in each season. This is because ESMA runs off the FES dataset, which assumes a slightly higher level of consumption (likely due to a higher level of losses experience in the real system).

Figure 5.3: Comparison of simulated and historical generation mix by season in 2015. Source: ESMA and (National Grid, 2015c).



Figures 5.4 and 5.5 demonstrate how ESMA dispatches different types of generators in the summer and winter days.

Figure 5.4: Comparison of hourly simulated and historical generation profiles for summer days in 2015. Source: ESMA and (National Grid, 2015c).

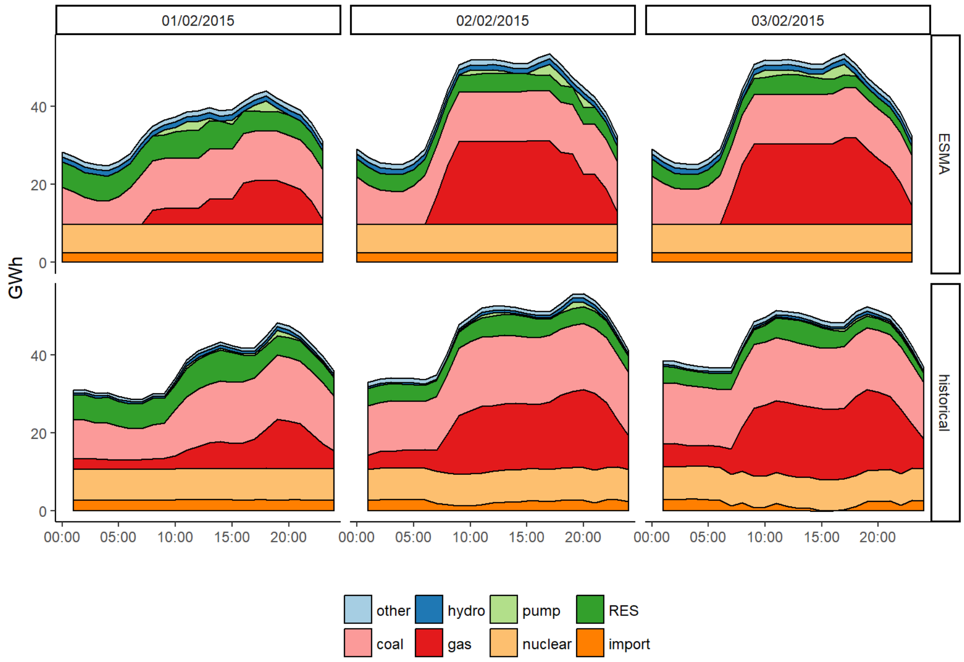


In the summer, it is visible how the model underutilises gas power plants whilst compensating by coal and pumped storage (Figure 5.4). In addition to the issue of static fuel prices, the shape of the modelled demand curve could explain the difference in historical generation mix and that modelled by ESMA. A slightly lower demand at night and a slightly higher peak during the day, mean that it is cheaper for ESMA to run coal and switch on the gas only for a few hours during the day in combination with pumped storage.

Similar observations can be made in the winter days, where the model does not run gas overnight (Figure 5.5). ESMA also seems to allow a sharper ramping of the gas generators, e.g. 2nd February. Finally, historical imports fluctuate throughout the day, whereas in ESMA imports are assumed to be constant throughout the year (see Section 3.4.5.3).

These observations highlight the limitation of ESMA, which models each technology as one large power plant generating electricity at short run unavoidable cost,

Figure 5.5: Comparison of hourly simulated and historical generation profiles for winter days in 2015. Source: ESMA and (National Grid, 2015c).

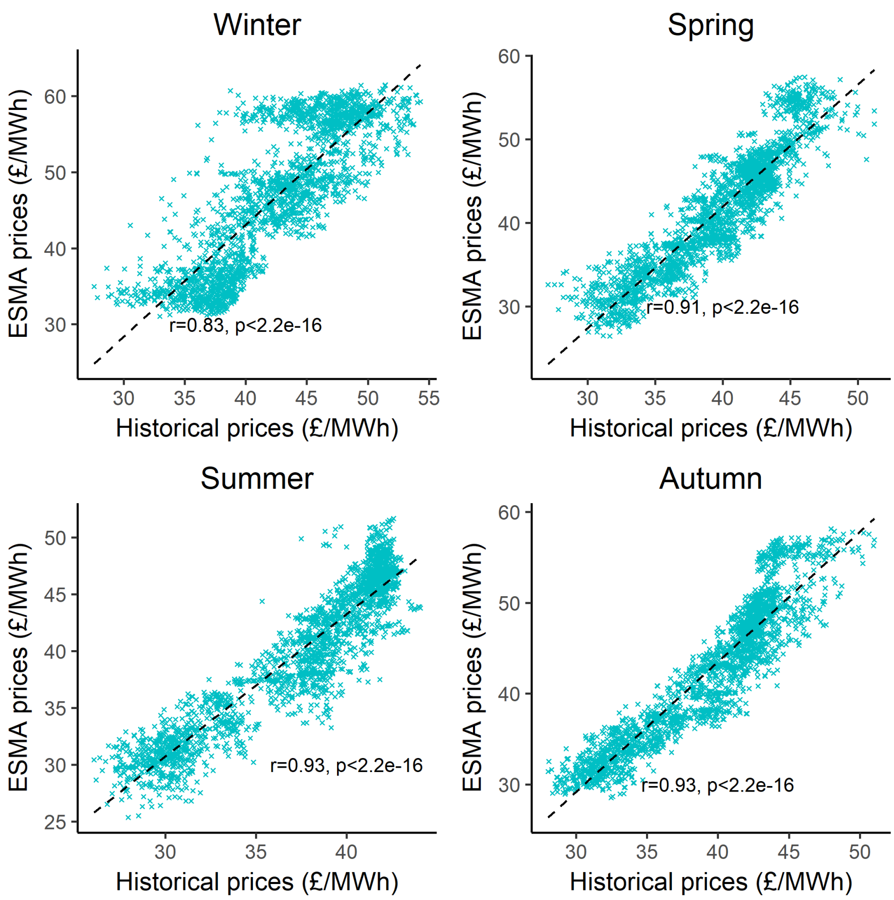


rather than many small heterogeneous generators. In addition to this, many operational details such as (ramping time, part load, spinning reserve, etc.) are not modelled. However, on the whole the shape of the generation curve and the priority of the technologies chosen by ESMA appear to resemble historical data within acceptable limits. An improvement to the model could be feeding more dynamic fuel prices and modelling multiple generators.

5.1.3 Electricity prices

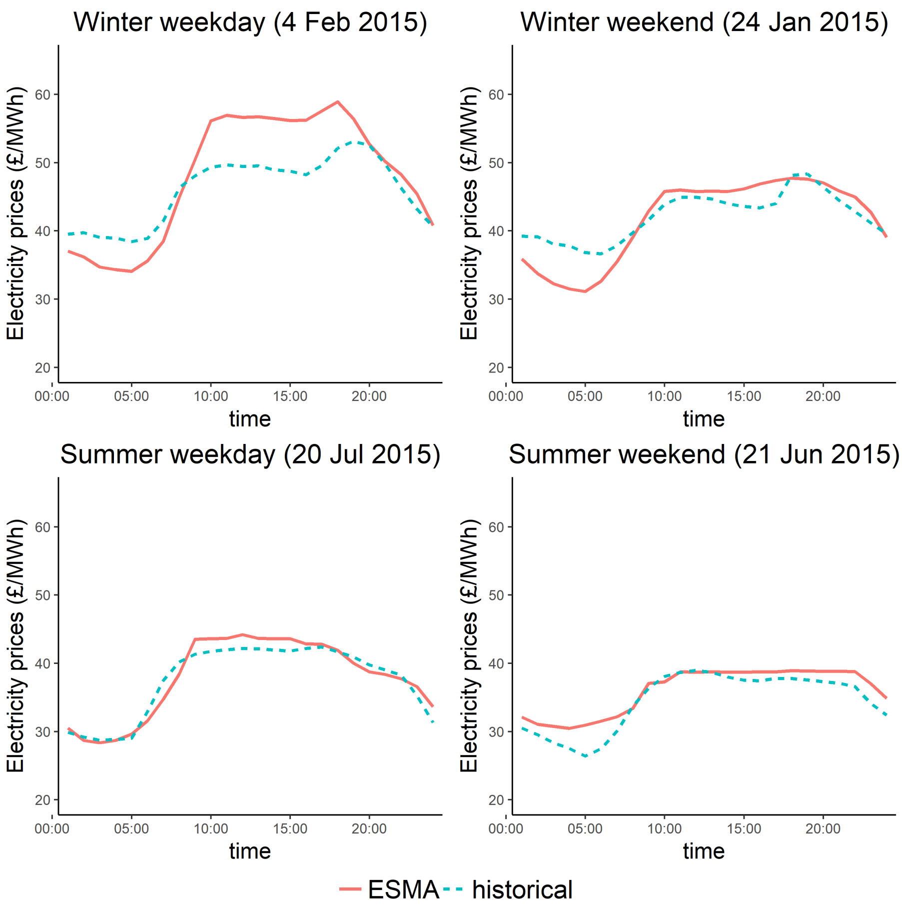
In the last part of historical data assessment, ESMA is tested in terms of recreating historical wholesale electricity prices taken from the exchange (APX Group, 2015). Similarly to system demand validation, analysis of hourly prices is performed for different seasons (Figure 5.6). It is noted that the noise in the exchange price data has been removed in order to obtain a cleaner demand-price relationship by fitting a polynomial to historical data (see Appendix E.1). This is justified by the fact that short term pricing includes many activities which do not relate to the pure cost of generating electricity, such as trading for arbitrage and hedging. The high correlation coefficients suggest a good agreement between simulated and historical prices.

Figure 5.6: Comparison of hourly simulated and historical electricity prices in 2015. Sources: ESMA and (APX Group, 2015).



In Figure 5.7, four exemplary days are assessed in terms of the shape of the price curves for historical and generated data. Overall, warmer days show a much smoother profile compared to the colder days. As a consequence of not modelling Economy 7 consumers, the observed prices are lower at night (i.e. between 00:00 and 06:00), which is especially noticeable in the winter on the 2nd February.

Figure 5.7: Comparison of hourly simulated and historical electricity prices for winter and summer days in 2015. Sources: ESMA and (APX Group, 2015).



5.2 Future Energy Scenarios

Similarly to validation against historical data, ESMA is assessed against FES data in terms of system demand, generation and prices. Here two boundary scenarios are considered (Steady state and Two Degrees+) as formulated in Section 4.

5.2.1 System demand

Although FES dataset does not offer an hourly demand curve, it does provide an annual demand peak which is compared to the modelled data in Figure 5.8. On the whole the two datasets are in good agreement with a discrepancy within a few GW.

In Figures 5.9 and 5.10, the consumption data is checked against FES data which is used by ESMA as an input. Having perfect agreement between ESMA and FES data output acts as a check that ESMA functions as expected.

Figure 5.8: Comparison of system demand peaks modelled by ESMA against FES for Steady State and Two Degrees+ scenarios in 2015-2050. Sources: ESMA and (National Grid, 2017a)

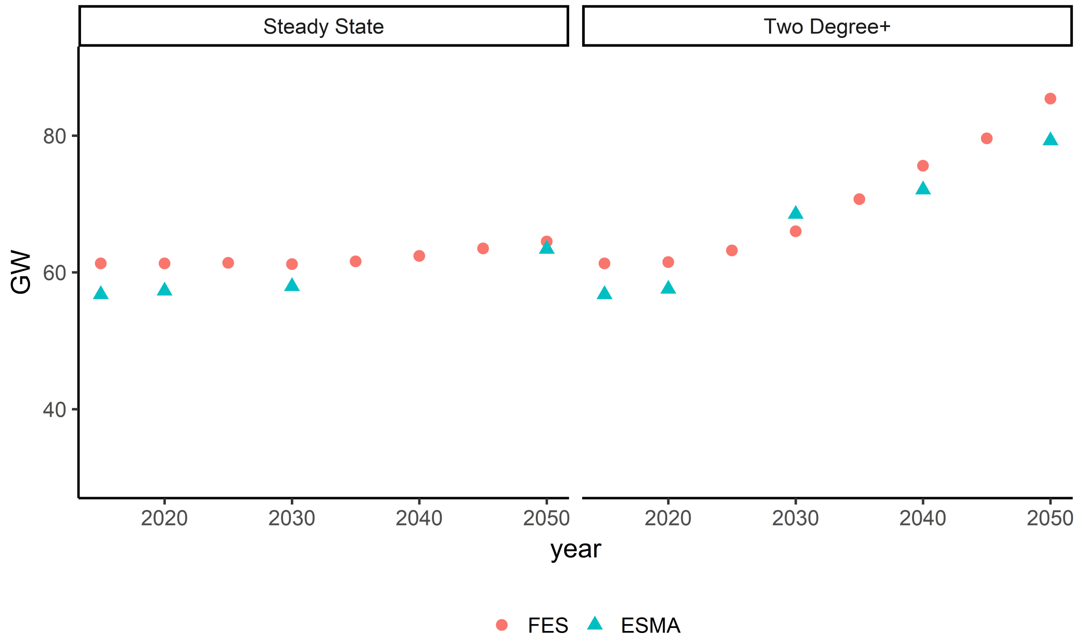


Figure 5.9: Comparison of electricity consumption modelled by ESMA and FES for Steady State and Two Degrees+ scenarios in 2030. Sources: ESMA and (National Grid, 2017a)

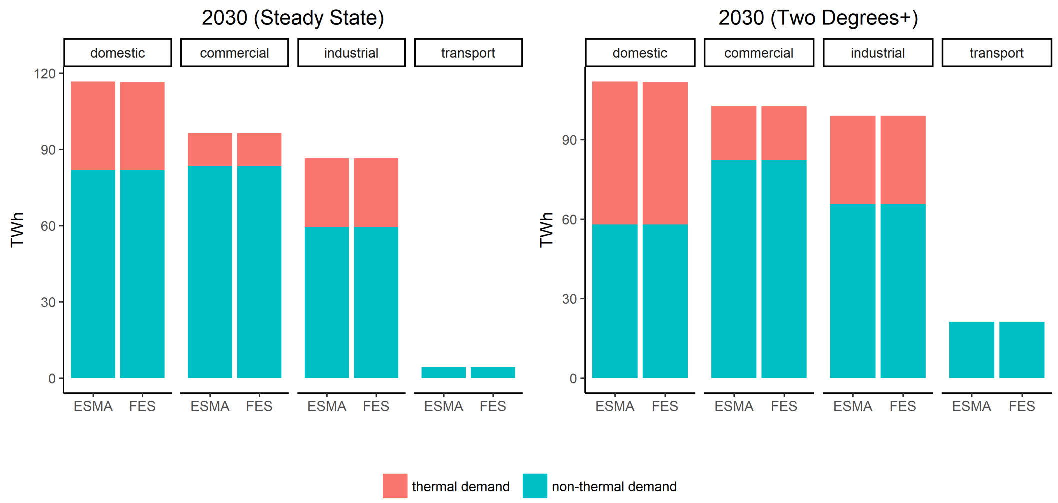
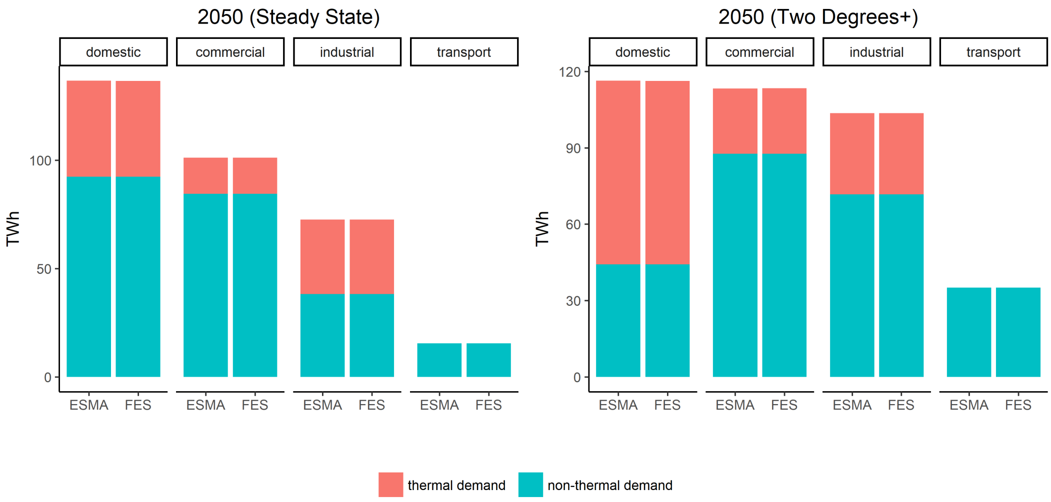


Figure 5.10: Comparison of electricity consumption between ESMA and FES for Steady State and Two Degrees+ scenarios in 2050. Sources: ESMA and (National Grid, 2017a)



5.2.2 Electricity generation

In Figures 5.11 and 5.12, the sources of generation utilised by ESMA are compared against the FES data for Steady State and Two Degrees+ scenario. For the Steady State scenario it can be seen that FES assumes a higher use of biomass and CHP. This is likely due to a high biomass price assumed in ESMA, as a result of which coal is prioritised over biomass generation. This highlights a limitation of the model which considers only one average price of biofuel. In reality, there are different types available in the market with a wide range of prices. Especially when modelling in the far future, it is difficult to predict the evolution of biomass prices, so the value has been fixed in the modelling environment. For the years 2030-2050, the generation mix seems to be in good agreement between ESMA and FES.

For Two Degrees+ scenario, FES dataset also contain a higher share of generation from biomass and a slightly lower share from gas. The rest of generation sources seem to be in good agreement. The discrepancies between the types of technologies used to generate electricity in FES and ESMA can be explained by different assumptions made for generator cost characteristics[1].

[1]This information regarding generation technology characteristics is not disclosed by the National Grid and so it is not possible to compare it to the assumptions made in this assumptions

Figure 5.11: Comparison of electricity generated by source from ESMA and FES under Steady State scenario, 2020-2050. Sources: ESMA and (National Grid, 2017a)

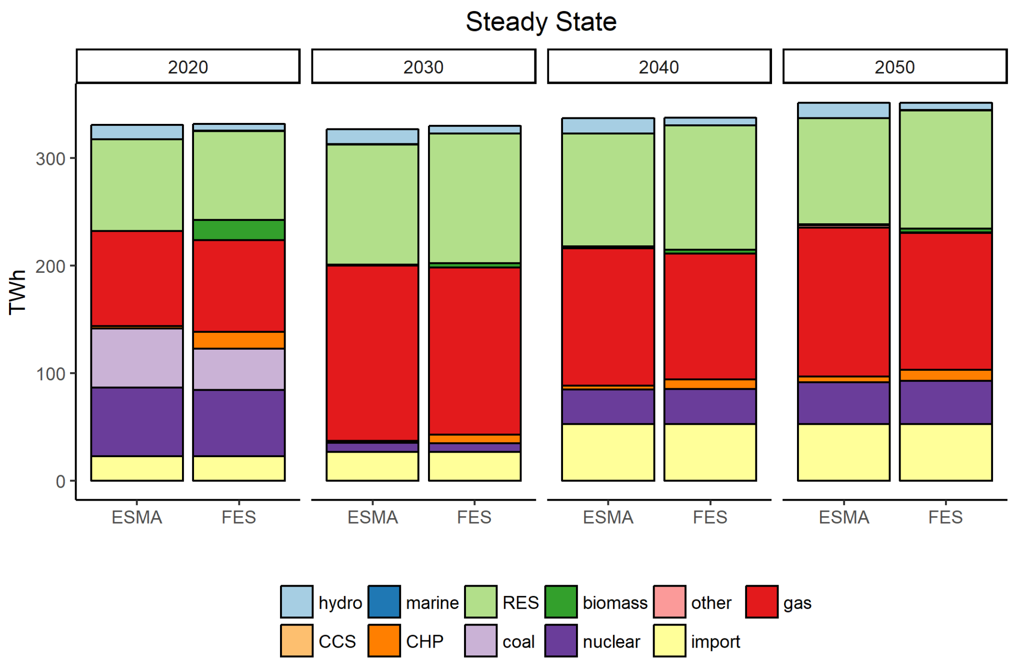
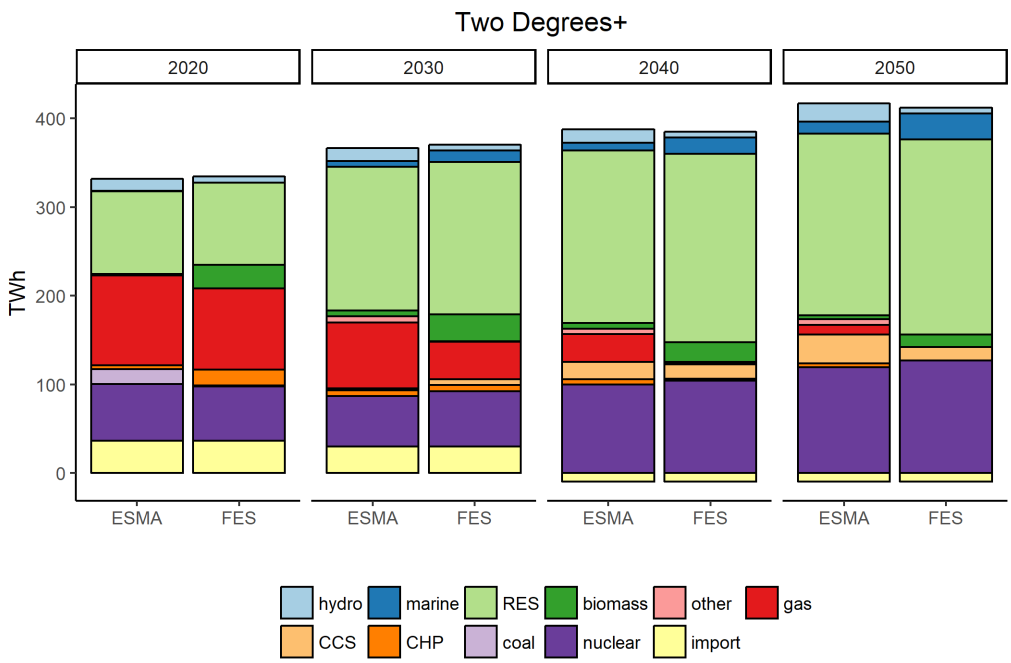


Figure 5.12: Comparison of electricity generated by source from the model and FES data under Two Degrees+ scenario, 2020-2050. Sources: ESMA and (National Grid, 2017a)



In Figures 5.13 and 5.14, the generation values from embedded solar are checked against FES data for different sectors. Perfect agreement between FES and ESMA datasets ensures that the model works as it should.

Figure 5.13: Comparison of electricity generation from embedded solar between modelled and FES data for Steady State and Two Degrees+ scenarios in 2030.

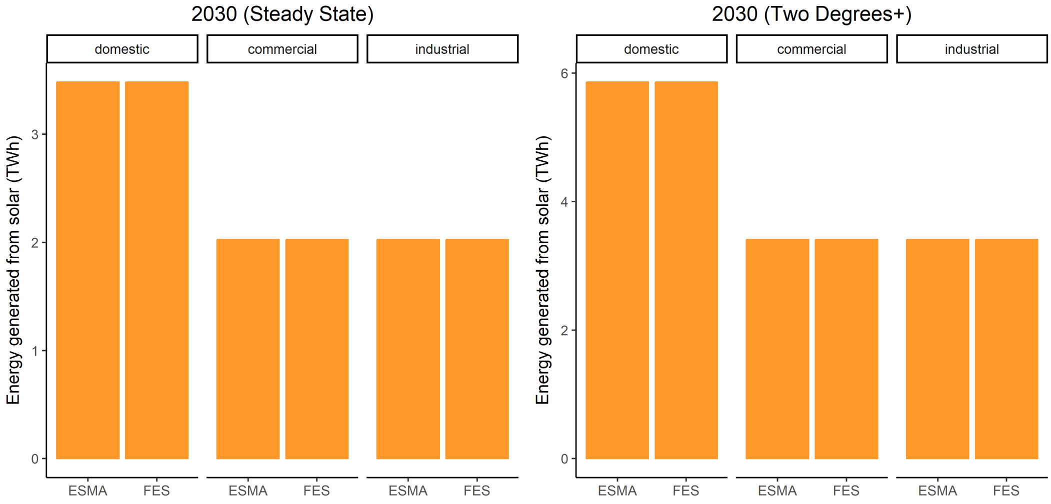
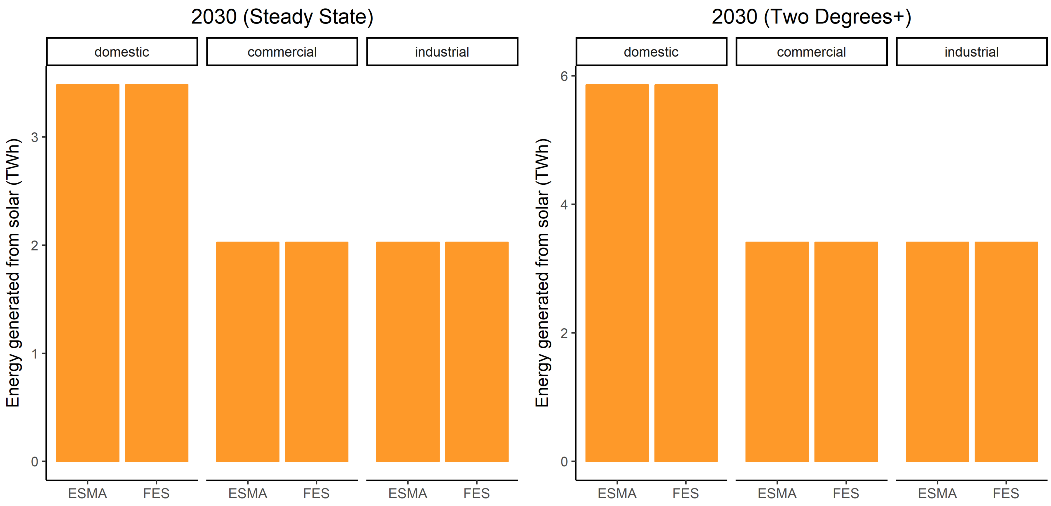


Figure 5.14: Comparison of electricity generation from embedded solar between modelled and FES data for Steady State and Two Degrees+ scenarios in 2050.



In Table 5.1 we summarise the differences between ESMA and FES modelling frameworks, which lead to the above discussed differences in observations.

Table 5.1: Comparison of assumptions made in ESMA versus FES model.

Assumption component	**FES**	**ESMA**
Gas supply and demand	Imports are available when required	Gas network not modelled
Renewables support mechanism	Renewable obligations until 2017 and Contracts-for-Difference after	Not considered
Capacity Market	All scenarios include the results from auctions completed before, and including, the T-1 Auction held in February 2017	Not considered
Exchange rates	Fixed profile across all scenarios for exchange rates with US dollar and the euro.	Fixed at 2017 level
Oil, gas and coal price	A single price forecast across all scenarios and fixed across the year	Same as in FES
Biomass and nuclear price	[Information not available]	Calculated based on (DECC, 2012; BEIS, 2016) (see Appendix C.1)
EU emissions trading scheme	Base prices for the EU ETS are used in all of the scenarios and fixed annually	Same as in FES
Population	A fixed profile is applied across all scenarios - reaching approximately 75 million by 2050	Growth rate same as in FES
Generation capacities	All scenarios are in line with the Government's policy to remove all unabated coal from the electricity generation mix by 2025	Same as in FES
Renewable generation profiles	[Information not available]	Average profiles obtained from (Pfenninger and Staffell, 2016)
Distributed energy resources	Depends on the level of prosperity assumed in the scenario	Same as FES
Electricity demand profiles	[Information not available]	Taken from (Elexon, 2017a)
Heating profiles for non-domestic consumers	[Information not available]	Calculated based on seasonal differentials in demand
Heating profiles for domestic consumers	[Information not available]	Taken from (Cambridge Energy, 2017)

5.3 Sensitivity analysis

Figure 5.15 demonstrates the results of the sensitivity analysis performed in 2017 (Steady State). Each parameter in the left column is varied from the default value by +/- 25% and the impact is reported in terms system cost and greenhouse gas (GHG) emissions as a percentage change relative to the default case.

Figure 5.15: Sensitivity analysis, 2017 (Steady State). Source: ESMA.

	Base case (no coordination)			
	25% increase		25% decrease	
	System cost	GHG emissions	System cost	GHG emissions
Non-deferrable demand	43.19%	21.07%	-30.97%	-25.35%
Gas price	3.00%	0.0002%	-3.00%	-0.0021%
Gas capacity	2.47%	-0.002%	-2.47%	0.001%
Coal price	-0.001%	-0.002%	0.13%	0.25%
Coal capacity	-2.52%	8.50%	3.08%	-10.35%
Wind capacity	-1.45%	-3.52%	1.48%	3.41%
Solar capacity	-0.22%	-0.34%	0.22%	0.34%
EV capacity	0.01%	0.01%	-0.01%	-0.01%
HP capacity	0.24%	0.14%	-0.24%	-0.14%
RH capacity	9.88%	5.25%	-8.72%	-5.41%
Pump storage capacity	-0.13%	0.71%	0.13%	-0.74%
Carbon price	0.01%	0.000005%	-0.01%	0.0001%

The model appears to be most sensitive to the level of non-deferrable demand, experiencing over 40% change in system cost and GHG emissions as a result of 25% change in total non-deferrable demand. As expected, higher demand leads to an increase in system cost and GHG emissions, whereas decreasing demand by the same amount leads to the opposite effect. The effect is not symmetric.

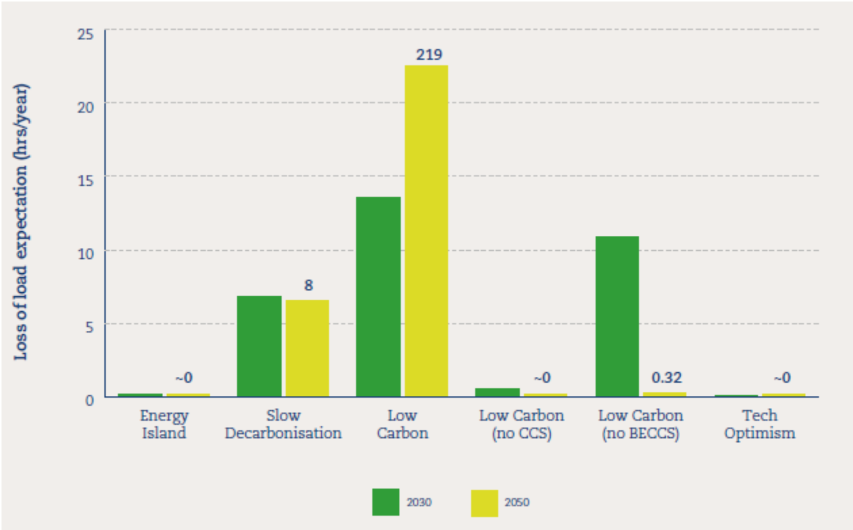
The other two parameters which noticeably influence the model are coal and wind capacity leading to 5-16% fluctuations in GHG emissions and a few percentage change in the value of system cost, as a result of 25% change in the parameter value. As expected, the level of emissions increases as wind capacity goes down and coal capacity goes up and vice versa. Changing capacity of resistance heating (RH) by 25% leads to a 5% change in system cost and GHG emissions. This is explained by the fact that heating electrification leads to an increase in total demand for electricity in the system. The rest of the parameters have a minor impact on the system cost and GHG emission level.

Comments on validation: Although important to assess against a different model output, the projections are done far in the future and so slight discrepancies between FES and ESMA data are deemed acceptable. The validation process has been able to show that ESMA is successful in recreating historical data as well as being in good agreement with the National Grid model for future energy scenarios. Certain limitations of ESMA have been discussed, however the reader is reminded that the focus of this work is to investigate the issues of system control and cost allocation to different types of consumers in the context of DSM, and so a slight deviation of modelled output from historical and FES data is deemed acceptable.

One important difference between ESMA and the FES model is that the latter includes gas network modelling, whereas the former doesn't. Considering that around 40% of electricity demand in the UK is met by gas-fired power plants (often the marginal source of generation), gas and electricity networks are closely interconnected for this market (DECC, 2015). Hence, gas demand profile can strongly influence the dispatch of generation resources and the price of electricity for end-users. An assessment, produced by the UK Energy Research Centre, concludes that electricity and gas system reliability in the UK can be significantly improved through investing in system flexibility (Watson et al., 2018). The report demonstrates the importance of demand side response and natural gas storage on reducing loss-of-load expectation (LOLE) and Expected Energy Unserved (EEU) (Figures 5.16 and 5.17. In fact, the introduction of a gas storage equivalent to the decommissioned Rough facility led to as much as 50% reduction in EEU (from 219 mcm to 105 mcm) relative to the business-as-usual scenario in the Low Carbon scenario in 2050. The effect on LOLE is stronger in 2030 leading to a drop from $\tilde{1}$3.5 hrs/year to just over 5 hrs/year.

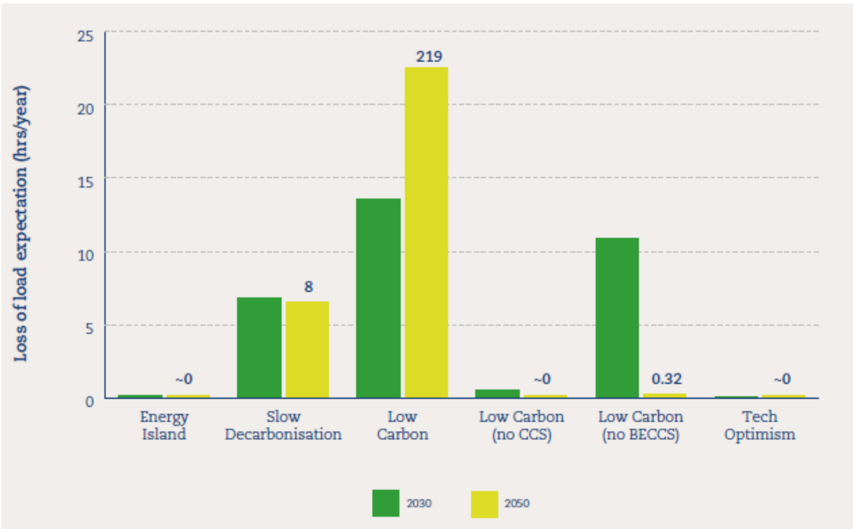
A number of researchers state the importance of modelling the electricity and gas networks together (Chaudry et al., 2014). This leads to a more accurate rep-

Figure 5.16: Gas system LOLE in 2030 and 2050. Source: (Watson et al., 2018).



Data labels show EEU in 2050 (mcm). Peak daily demand in 2016 is 370mcm

Figure 5.17: Impact of additional gas storage capacity on gas system LOLE. Source: (Watson et al., 2018).



Data labels show EEU in 2050 (mcm). Peak daily demand in 2016 is 370mcm

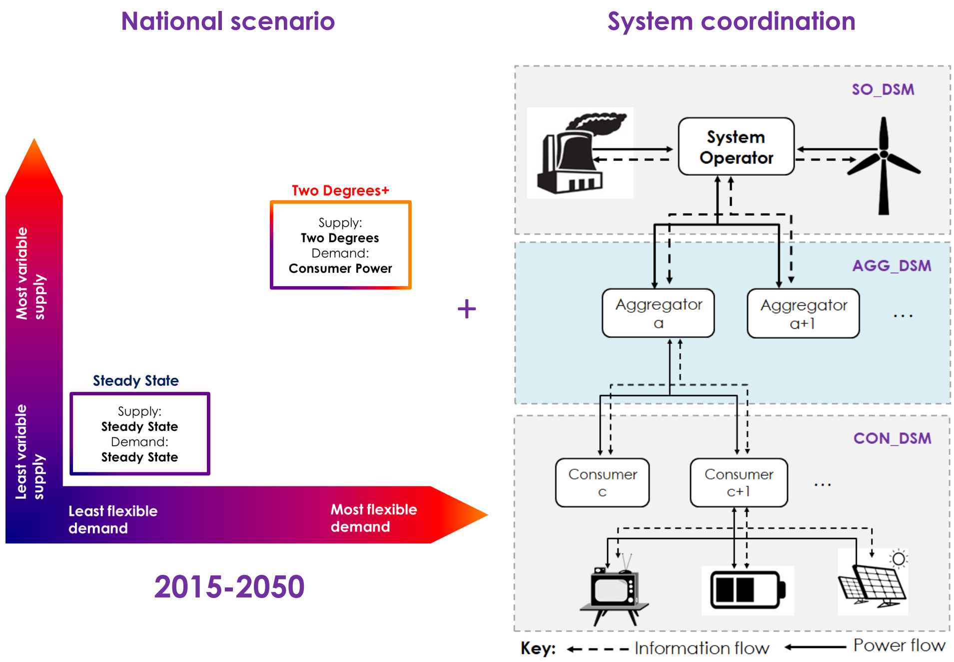
resentation of flexibility services (especially when district heating it considered), power price determination and scheduling of supply resources. However, it does significantly complicate the modelling framework. Considering the aim of this research and time availability to deliver it, the modelling of the gas network is left outside of the scope of this work.

Chapter 6

Results and discussion

As per the scenarios constructed in chapter 4, the impact of DSM is analysed in the context of the British electricity grid at three hierarchal levels for two national scenarios for the period 2015-2050 (Figure 6.1).

Figure 6.1: Combination of simulation scenarios.



To recap, two boundary scenarios for the evolution of the British electricity system are considered: the least variable and flexible (identified as Steady State) and the most variable and flexible (identified as Two Degrees+). For each of the national scenarios, the long-term impact on the electricity system is explored when consumer demand is managed by stakeholders from one of the three hierarchal layers: consumer, aggregator and the System Operator (referred to as the *DSM regime*).

The impact of each DSM regime is measured by tracking the changes in electricity cost (for the system and consumers), demand and the level of greenhouse gas (GHG) emissions relative to the case when all stakeholders are passive (referred to as the *base case*) for snapshot years 2015,2030 and 2050. The analysis is split into three parts based on the type of coordination taking place.

In part one, the simplest form of DSM is assumed by deploying algorithm CON_CM, whereby consumers pursue own selfish objective of minimising the cost of electricity based on the real-time price (RTP)(see 3.5.1). We explore the extent to which this approach is beneficial to the grid and the threshold point at which consumer herding towards the same periods of low electricity prices can be harmful to the system, leading to increased system cost and greenhouse gas (GHG) emissions.

In part two, the consequences of *aggregator-led DSM* are investigated, whereby aggregators instruct consumers on how to schedule. Firstly, we consider a model where aggregators serve the grid through deploying algorithm AGG_DF and demonstrate the benefits of a well-coordinated DSM to the system as well as individual consumers. We then look at the case where aggregators become aggressive and use demand scheduling to actively minimise the cost of purchased power from the grid. Similarly to part one, we explore the threshold at which 'herding' of aggregators towards low prices can lead to negative consequences for the system. Part two is concluded by demonstrating how aggregator herding can be overcome through centrally controlled DSM. For this algorithm SO_CM is deployed, whereby the System Operator communicates with the aggregators and the market during the coordination process. The two algorithms AGG_DF and SO_CM are compared in terms of financial savings to the grid and the amount of GHG emissions avoided due to the deployment of each DSM regime.

In part three we explore the possibility of a decentralised consumer DSM by developing algorithm CON_CM into CON_CM+ by means of introducing a damping term α which controls the strength of consumer response to real time electricity prices. We explore a range of potential outcomes under CON_CM+ regime by varying α as well as consumer participation rate in DSM (conDR). Algorithm CON_CM+ is then further enhanced by allowing consumers to learn α based on their daily bills, which renders a completely *autonomous decentralised DSM* regime CON_CM+(LEARN). The results chapter is concluded by comparing all DSM regimes: CON_CM+ (with and without learning), AGG_DF and SO_CM. The success of each algorithm is assessed in terms of the benefits it brings to the system as well as each individual consumer. The key point of discussion is the process of fairly allocating the benefits from DSM to different types of consumers considering that they have different resources and therefore level of influence on the wholesale electricity prices.

6.1 Part I: How far can dynamic pricing take us?

Informing consumers of the true electricity generation cost via dynamic prices (e.g. TOU or RTP) is often considered as a panacea to achieving more sustainable electricity consumption. A large pool of academic research reports on the benefits of dynamic pricing in terms of lowering system cost, consumer bills and system emissions (Zakariazadeh et al., 2014; Houwing and Ilic, 2008). 'The Triad' scheme deployed in the UK is a perfect example of how information about real-time wholesale prices can help reduce system demand peaks and lower the cost of electricity generation (National Grid, 2015d). However so far, the proportion of consumers which participate in DSM has been relatively low, mainly limited to commercial and industrial end-users which are controlled by aggregators, e.g. KiWi Power and Enernoc (Power, 2018; Enernoc, 2018). In addition to this, studies assessing the impact of DSM rarely perform the analysis for the future, and so the full impact of DSM based on dynamic pricing has not been explored.

In order to engage domestic consumers, the UK government has set a target to equip every household with a smart meter by 2020 with the aim of informing end-users of their electricity usage and wholesale electricity prices in real time (Ofgem, 2018a). Yet, with a higher proportion of 'smart' and flexible end-users it may be a case that consumer response to RTP may lead to the creation of new demand peaks and increased electricity prices as a result of the market herding towards the same periods of low electricity prices. To elaborate, as consumers become informed of the hours when generation from renewables is high (and prices are low), they will aim to shift flexible demand to those periods in order to minimise the cost of electricity. Yet, if enough consumers act in a similar manner, the shifted demand will create new peaks in the system and as a consequence increase electricity prices. Such proactiveness on the demand side, may also make it harder for the System Operator to predict electricity demand and balance the grid.

Figures 6.2 and 6.3 demonstrate with a simulated data from 2030 under Two Degrees+ scenario how simultaneous cost minimisation by consumers can lead to more volatile system demand and electricity prices. Figure 6.2 demonstrates what happens to the daily electricity demand curve as more consumers (represented by conDR parameter) shift demand to period of low electricity prices (based on the day ahead wholesale price information). Hence, as consumers receive the same wholesale price information the react in a similar manner, which creates new demand peaks. A higher share of consumer adopting this simple strategy leads to a more extreme effect.

Such behaviour can result in suboptimal utilisation of renewable resources and consumer storage, increased demand peaks and ultimately lead to higher and more volatile electricity prices for the system and consumers (Figure 6.3). It is important to note that the effect of such consumer DSM strategy is exaggerated but it does highlight the limitation of the simple RTP-style demand response, where all consumer receive the same price information.

In order to investigate when herding might occur and what it might mean for the system, three snapshot years are modelled (2015,2030,2050) whereby consumers cost minimise by deploying algorithm CON_CM (see Section 3.5.1). We consider 0%, 50% and 100% consumer participation in DSM and track system cost, demand peaks and GHG emissions to evaluate the impact of this DSM regime on

Figure 6.2: Simulated system demand with different consumer participation in CON_CM, 11-13 April 2030 (Steady State). Source: ESMA

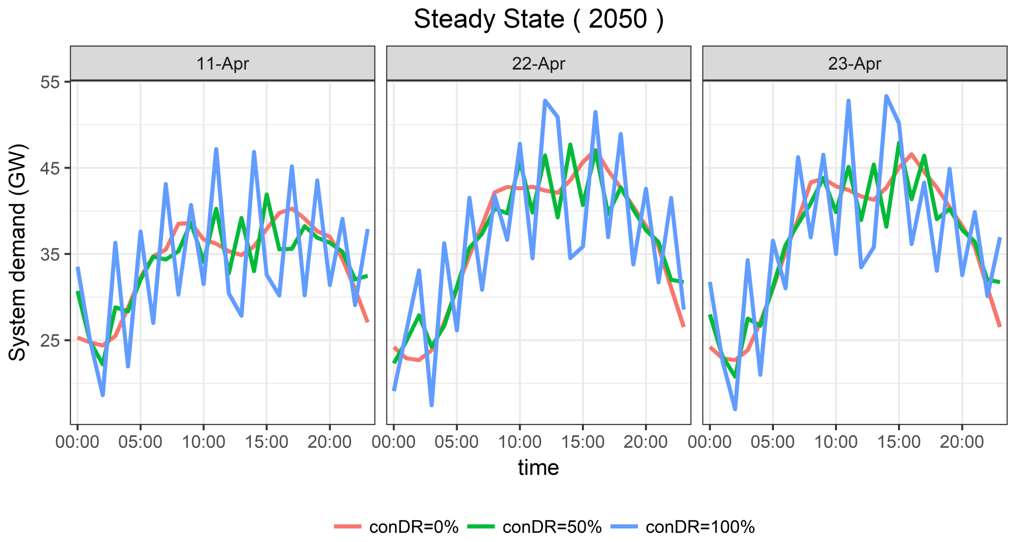
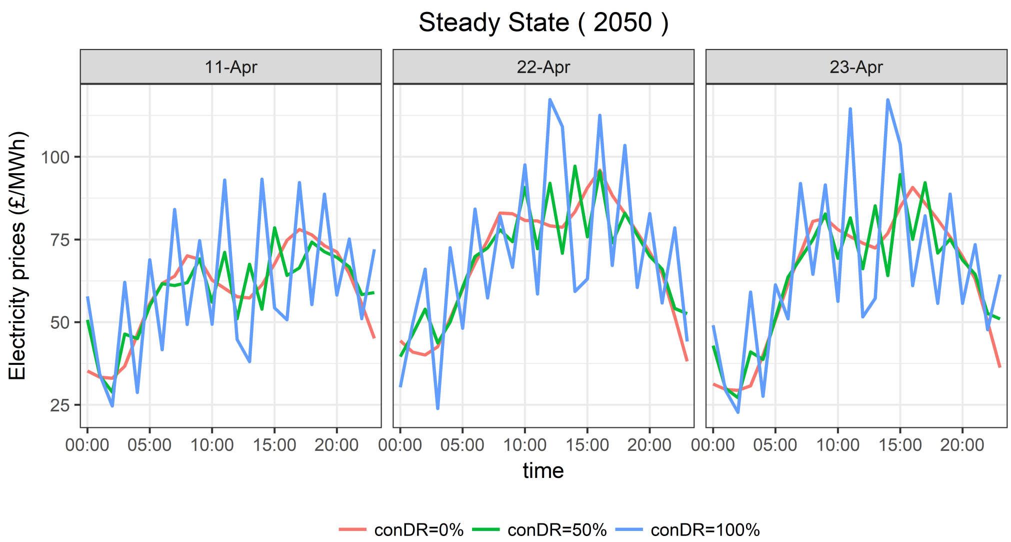


Figure 6.3: Daily system prices curve with different consumer participation in CON_CM, 11-13 April 2030 (Steady State). Source: ESMA

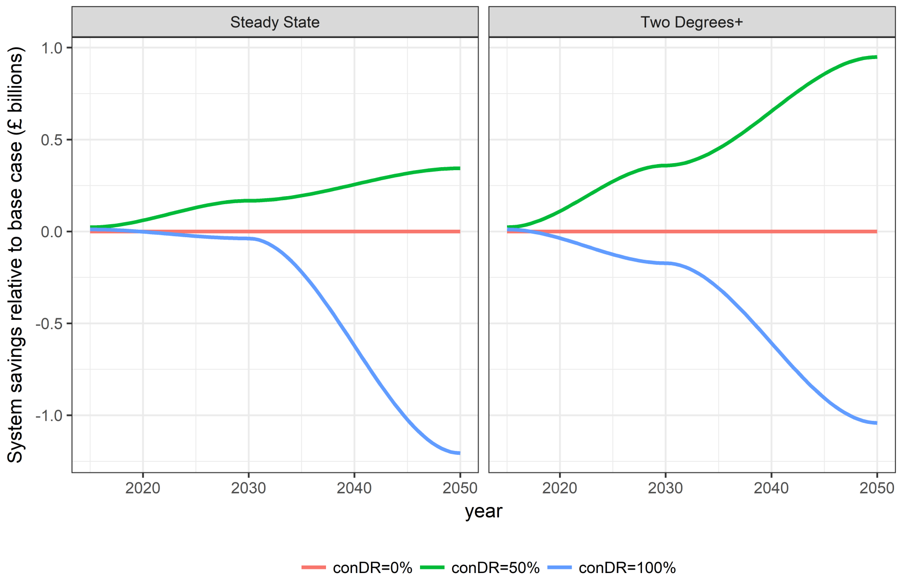


the system. The benefits of DSM are investigated for different types of consumers across four economic sectors (domestic, commercial, industrial and transport) by calculating how their electricity bills change relative to the base case (when consumers are passive).

6.1.1 System demand and costs

In order to assess the impact of the simplest form of DSM (i.e. CON_CM when consumers optimise independently based on the RTP), we calculate the difference in the annual system costs relative to the base case (when consumers are passive), which is referred to as *system savings*[1] (Figure 6.4). The reader is reminded that in the context of ESMA system cost reflects the short run avoidable cost of generating electricity and the cost of utilising the transmission and distribution network but does not include the capital costs of the grid infrastructure and balancing costs.

Figure 6.4: Annual system savings with CON_CM relative to the base case. Source: ESMA



Note: system costs include short run electricity generation costs and the use of the network but ignore capital costs of the grid infrastructure and the grid balancing costs.

The results (subject to the modelling assumptions) suggest that with 50% consumer participation level the system experiences savings, whereas with 100% consumer herding leads to system losses as early as 2020 in Two Degrees+ and 2030 in the Steady State scenario (as indicated by the negative values of savings on the chart). We note that prior to 2040 the system sees higher losses in the Two Degrees+ scenario (£173 million versus £38 million in 2030), whereas by 2050 the losses are higher in the Steady State scenario (£1.2 billion versus £1 billion). This can be

[1]Hence negative savings correspond to losses

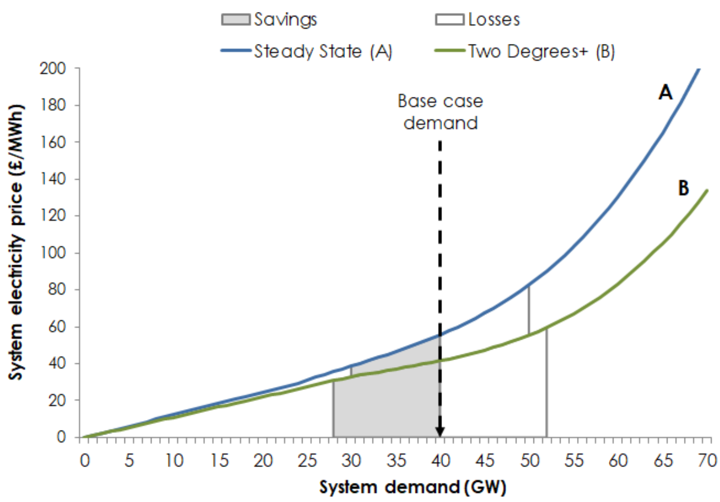
explained by the difference in the capacities of renewables and flexible consumer technologies assumed in each scenario.

More consumer flexibility and a lower level of renewables (hence a steeper price curve) exaggerates the effect of DSM on system costs. On the contrary, a lower level of consumer flexibility and renewables in the grid (hence a shallower price curve) dampen the effect of DSM, as consumers see less financial benefit from shifting demand. However when there is a combination of low renewables and low system flexibility (such as in Steady State scenario), or high renewables and high system flexibility (such as in Two Degrees+ scenario) we see a combination of these effects.

Figure 6.5 demonstrates how savings and losses are made under Steady State (line A) and Two Degrees+ (line B) for an exemplary hour in 2050. Due to higher system flexibility assumed in the Two Degrees+ scenario (line B), system demand is able to deviate more from the base case when DSM is deployed. It is noted that the difference in prices between the two scenarios is higher to the right side of the base case line (i.e. in the case of losses) compared to the left side (i.e. in the case of savings). When the system saves, higher flexibility in the Two Degrees+ scenario overshadows the effect of marginally higher prices assumed for the Steady State scenario leading to larger savings. On the contrary, when the market herds and the system experiences losses the difference in the price level becomes more significant and losses are higher under Steady State scenario.

As a result of this interplay between system parameters, prior to 2040 more system flexibility in the Two Degrees+ scenario overshadows the relative contribution from renewables on keeping prices low and the observed losses are higher compared to the Steady State scenario. Post 2040, consumer flexibility catches up in the Steady State scenario and coupled with a steeper electricity price curve, results in higher system losses compared to the Two Degrees+ case. Using the same logic it is possible to explain why savings are higher in the Two Degrees+ scenario compared to the Steady State case, i.e. when 50% of consumers participated in CON_CM. Across the two national scenarios maximum system losses reach £173

Figure 6.5: Demonstration of system losses and savings with CON_CM calculated for an exemplary hour, 2050. Source: ESMA



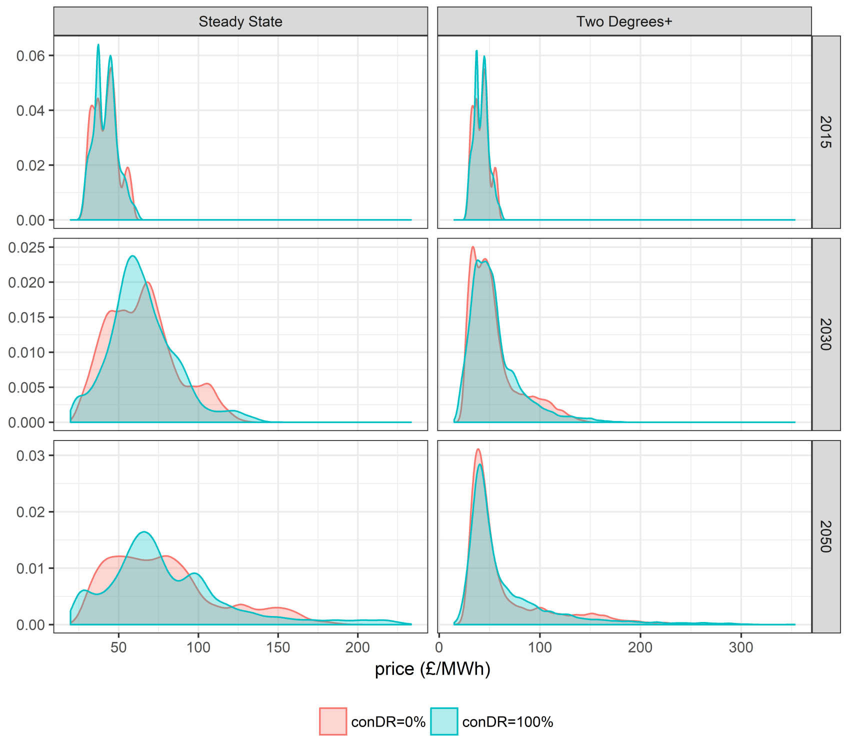
million per year in 2030 and £1 billion per year in 2050.

Figure 6.6 demonstrates the effect of consumer cost minimisation on the wholesale electricity prices.

In 2015 the system benefits from a 0.2% drop in the average value and a 5% drop in the volatility of the wholesale prices, which is in-line with the earlier observations regarding system savings. In 2030 it is possible to see a marginal reduction in the volatility as well as the mean price in the Steady State scenario due to a limited capacity of flexible consumer resources. For the remaining years, 100% consumer participation in CON_CM leads to higher and more volatile prices. In 2050 the annual wholesale price volatility increases by almost 12%, whereas the mean goes up by 3.4% in the Steady State scenario. For Two Degrees+ the negative consequences of herding on the prices are lower, as a result of higher renewable capacity in the system and lower prices as a whole.

Due to the limitations of the generation component in ESMA, looking only at the wholesale prices does not provide the full picture of the impact of DSM on the system. For this reason, the annual system demand peak is observed, as it determines the network and reserve capacity requirements in the grid. Figure 6.7 demonstrates how the annual system demand peak changes as more consumers cost minimise with CON_CM. With 50% participation level system peak

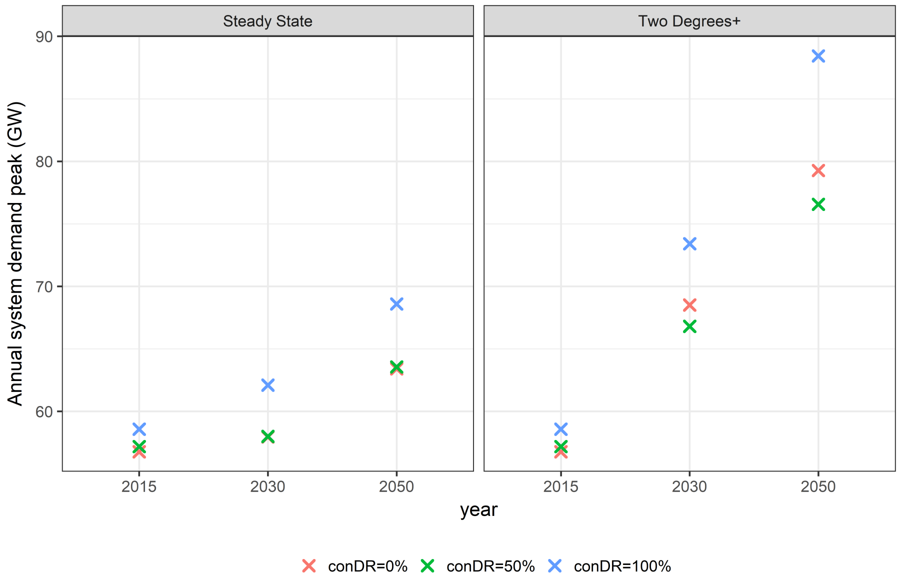
Figure 6.6: Wholesale price distributions with and without CON_CM, 2015-2050. Source: ESMA



Statistic	DSM / Year	Steady State: Base case (conDR=0%)	Steady State: AGG_DF (conDR=100%)	Steady State: % change	Two Degrees+: Base case (conDR=0%)	Two Degrees+: AGG_DF (conDR=100%)	Two Degrees+: % change
Mean (£/MWh)	2015	43.9	43.8	-0.2%	43.9	43.8	-0.2%
	2030	70.6	70.4	-0.3%	60.8	61.0	0.3%
	2050	88.2	91.2	3.4%	76.6	78.9	3.0%
SD (£/MWh)	2015	7.7	7.3	-4.9%	7.7	7.3	-4.9%
	2030	21.6	20.9	-3.1%	24.2	24.5	1.3%
	2050	34.7	38.8	11.8%	41.4	45.2	9.3%

decreases in the Two Degrees+ scenario, however with 100% consumer participation (conDR=100%) annual demand peak is increased immediately. The need for extra network capacity and generation reserve as a result of herding amounts to 4.1GW and 4.9GW in 2030 increasing to 5.2GW and 9.2GW by 2050 in the Steady State and Two Degrees+ scenarios respectively.

Figure 6.7: Annual system demand peak with CON_CM, 2015-2050. Source: ESMA

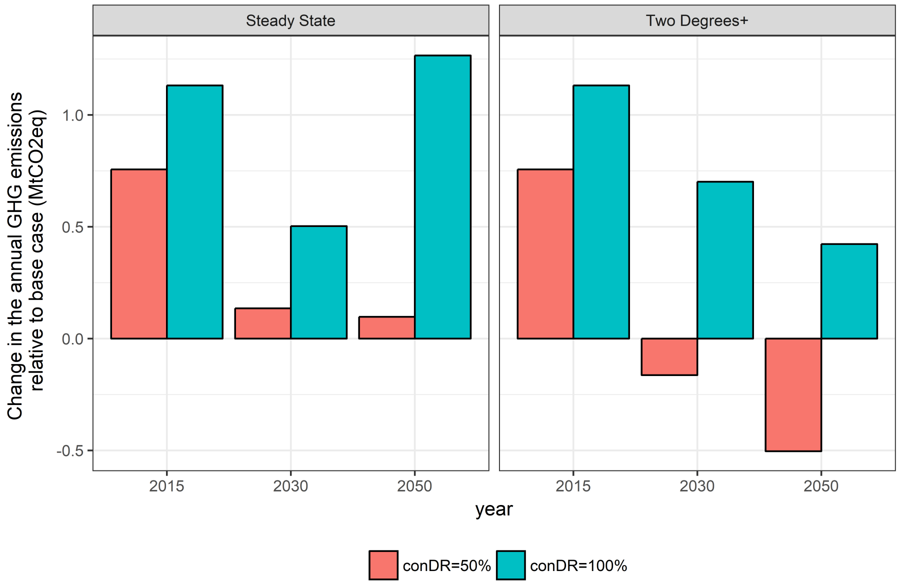


6.1.2 System GHG emissions

Not surprisingly herding has a negative effect on the level of greenhouse gases (GHGs) emitted by the electricity system. Figure 6.8 shows the absolute change in the annual level of GHGs relative to the base case as more consumers cost minimise. In fact, the system sees an increase in GHG emissions immediately even with 50% consumer participation level (when financial savings were observed to be positive). Only in the Two Degrees+ (2050) scenario with conDR=50% does the system benefit from a reduction in the level of GHGs. These observations suggest that in the Steady State and the earlier years of the Two Degrees+ scenario, reducing the cost of electricity generation does not necessarily mean decreasing the amount of GHGs emitted by the system. This happens for two reasons. Firstly, the system uses more energy when utilising storage which is not 100% efficient. Secondly, the CO2 price is lower in earlier years (especially in the Steady State scenario), meaning that the system chooses more flexible but polluting sources of generation.

Figure 6.9 shows the change in the generation mix relative to the base case in 2030 and 2050 for the two national scenarios, where a positive value indicates an increase in the use of particular generation technology and a negative value a decrease. As expected, increased consumer participation in CON_CM leads to a higher level

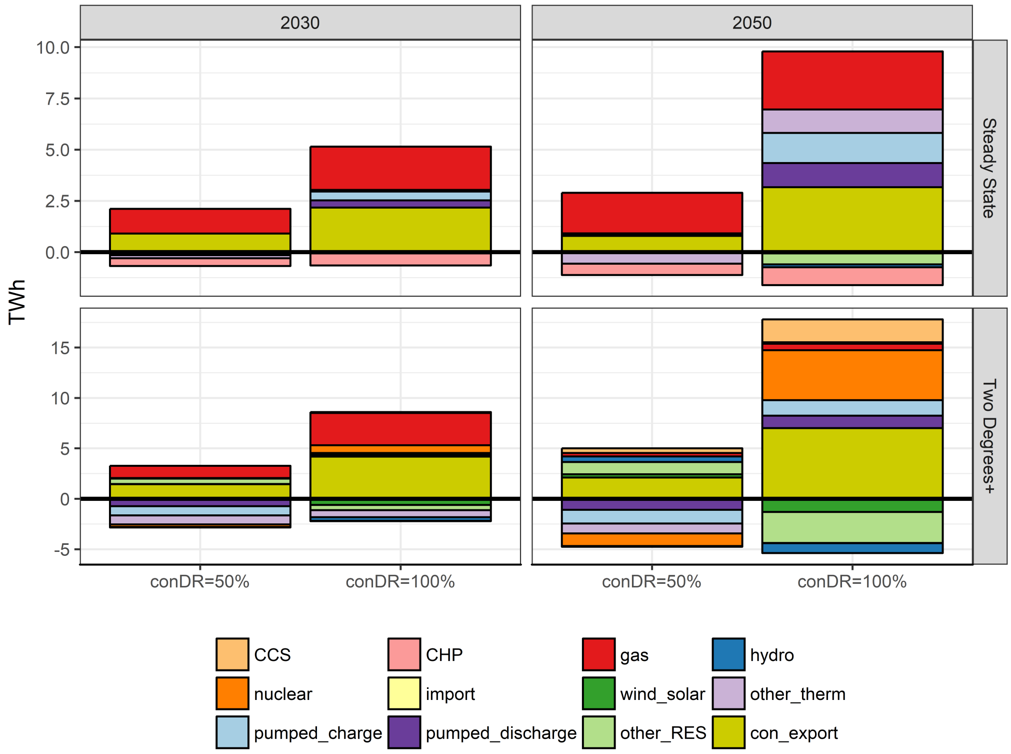
Figure 6.8: Change in the annual level of greenhouse gas emissions with CON_CM relative to the base case, 2015-2050. Source: ESMA



of generation in the system, met by consumer exports (solar and storage discharge[2]), thermal generators (Steady State scenario), CCS and nuclear (Two Degrees+), and pumped storage. This comes as a result of losses originating from the use of consumer and system storage which is not 100% efficient. The amount of consumer exports goes up with increased level of participation as more consumers aim to sell electricity when the projected wholesale price for it is high. When conDR=50%, CON_CM has a net positive effect on the fuel mix in the Two Degrees+ scenario leading to a decrease in the amount of energy generated from 'other_therm' generators (mainly diesel and fuel oil) and pumped storage. However when conDR=100%, the system utilises more thermal generation in order to accommodate for a demand pattern with sharper peaks and troughs. Consumer herding also leads to the curtailment of renewable energy as the system struggles to balances highly volatile consumer demand which is not correlated with variable supply. This is especially noticeable in 2050 Two Degrees+ scenario, where total curtailment of hydro, wind, solar and other renewables amounts to over 11GWh when all consumers cost minimise.

[2]Partially fuelled by an increase in transmission level generation.

Figure 6.9: Change in the electricity generation mix by source with CON_CM relative to the base case, 2030 and 2050. Source: ESMA

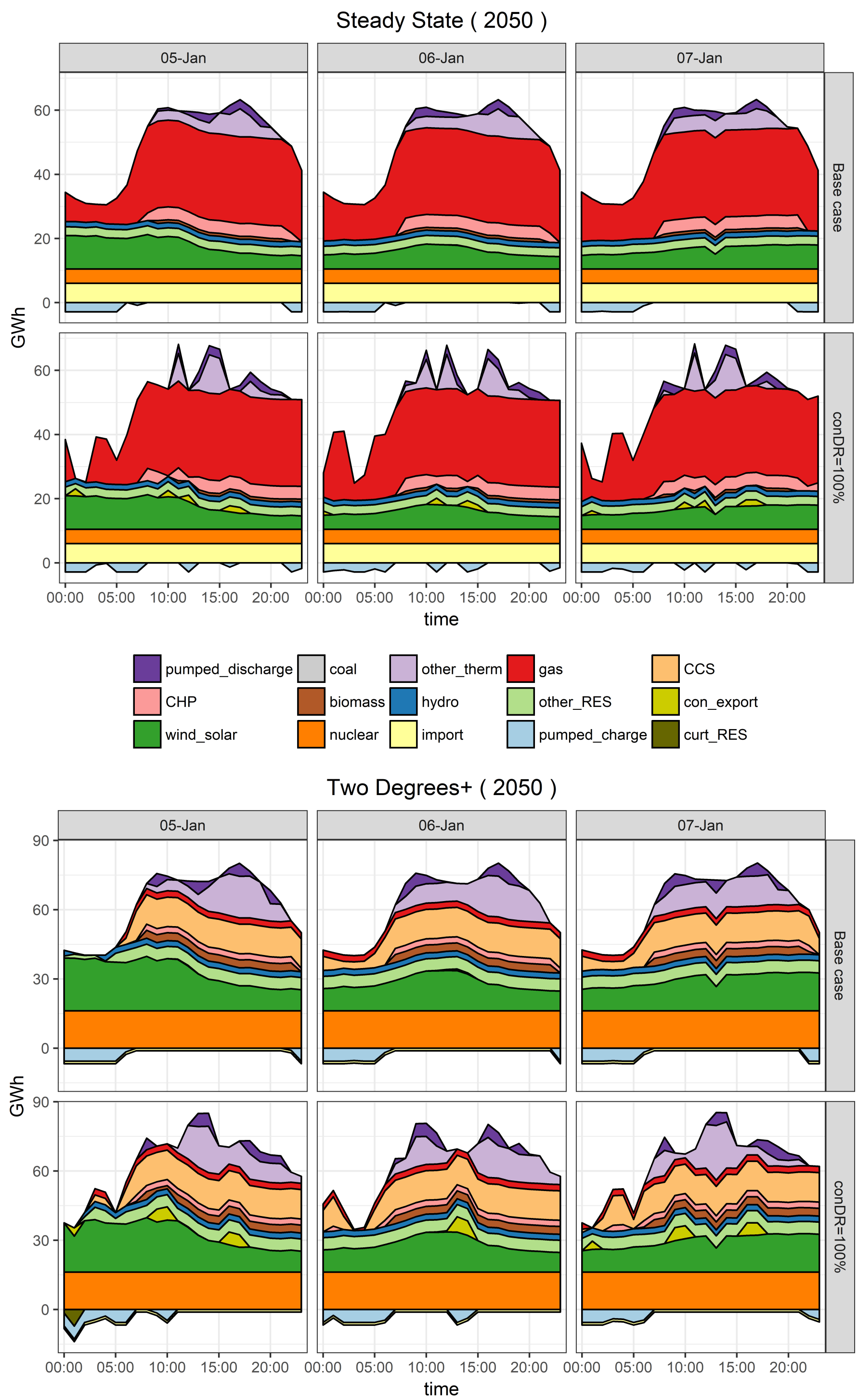


Note: 'other_therm' includes open cycle gas turbines (OCGT), diesel and gas reciprocating engines, and fuel oil 'other_RES' includes geothermal CHP, waste CHP, anaerobic digestion CHP, landfill gas, sewage, marine and biogas CHP

In Figures 6.10 and 6.11,we look at the daily generation profiles in 2050 in the winter and summer days in order to better understand how the generation pattern changes as a result of herding. In the winter, sharper demand peaks lead to a higher utilisation of flexible resources and pumped storage. It is possible to see the difference between the two scenarios, i.e. in the Steady State the model utilised mainly gas (red), whereas in the Two Degrees+ CCS, nuclear and renewables are the primary sources of generation. The utilisation of other thermals and pumped storage is similar in the two scenarios. One other difference is that in the Steady State the system imports (on average 6GWh per hour) whereas in the Two Degrees+ the system exports (on average 1.1 GWh per hour) electricity.

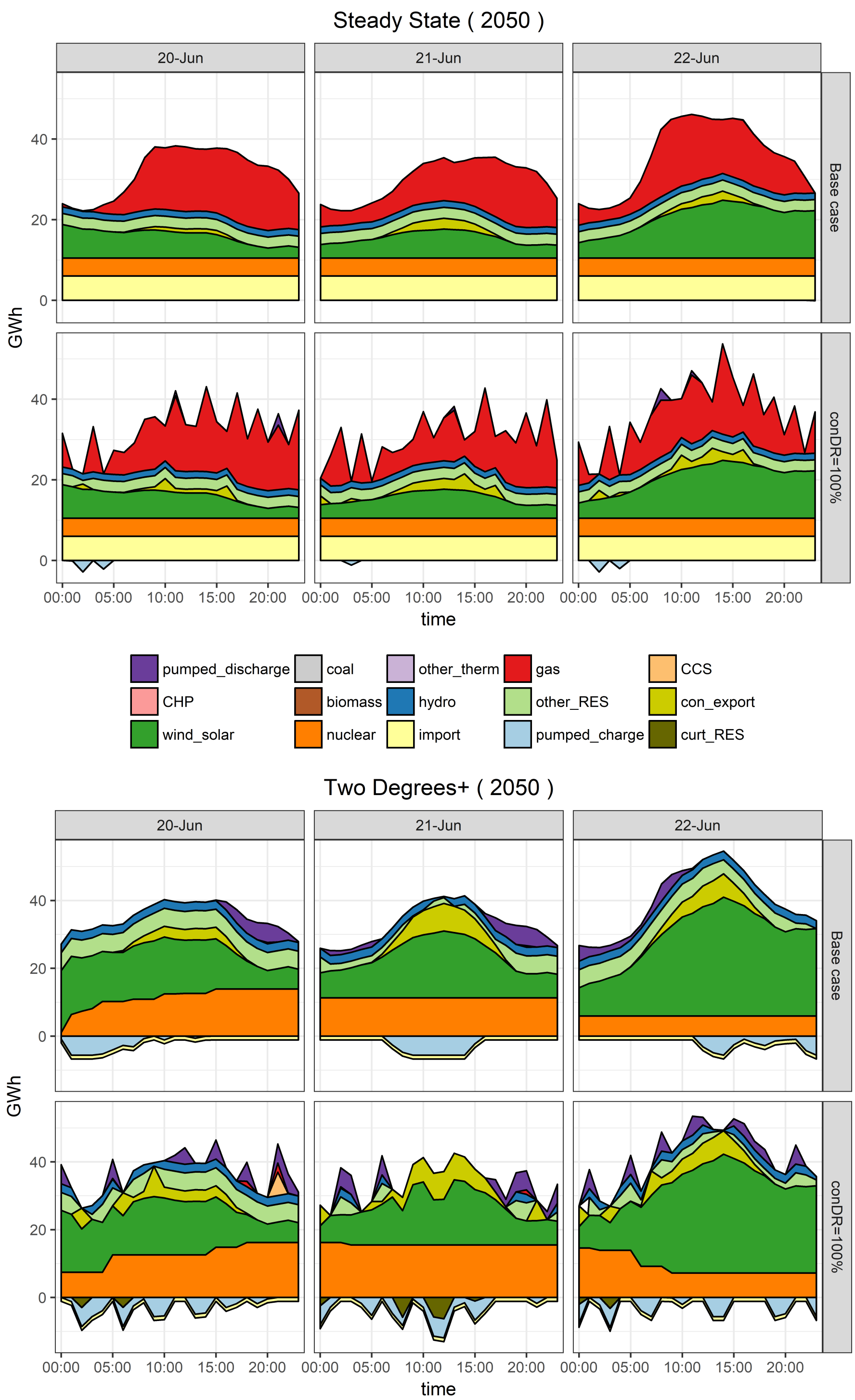
In the summer, both scenarios benefit from an increased renewable generation. As a result, in the Steady State scenario the system accommodated for a volatile demand curve (in the case of herding) by deploying gas generators compared to ‘other them’ used in the winter. In the Two Degrees+, scenario increased level of consumer exports leads to the curtailment of renewables as the system struggles to absorb the excess renewable generation. In contrast to the Steady State scenario, under Two Degrees+ the system utilises pumped storage (assumed to run at zero cost) in order to accommodate for a more volatile demand curve. We also note that the system starts to cycle nuclear generators in order prioritise the use of renewables even though it is assumed to be the most expensive technology to cycle.

Figure 6.10: Daily generation by source with and without CON_CM (conDR=100%), 5-7 January 2050. Source: ESMA



Note: 'other_therm' includes open cycle gas turbines (OCGT), diesel and gas reciprocating engines, and fuel oil 'other_RES' includes geothermal CHP, waste CHP, anaerobic digestion CHP, landfill gas, sewage, marine and biogas CHP

Figure 6.11: Daily generation by source with and without CON_CM (conDR=100%), 20-22 June 2050. Source: ESMA



Note: 'other_therm' includes open cycle gas turbines (OCGT), diesel and gas reciprocating engines, and fuel oil
'other_RES' includes geothermal CHP, waste CHP, anaerobic digestion CHP, landfill gas, sewage, marine and biogas CHP

A note on generation model limitations. One of the limitations of the market component in ESMA is that it does not penalise the generators for rescheduling on the day. In reality, if a generator is scheduled to run for the day-ahead it incurs an additional cost if it is required to change its schedule at short notice. In addition to this there is no cost imposed on curtailing renewables like hydro, wind and solar. As a result, the market is able to make use of these resources as it wishes. Hence, the real cost of herding is likely to be higher than what has been shown here, especially if the additional network and reserve requirements are considered. Nevertheless, it is clear from our observations that herding due to consumer cost minimising behaviour can lead to some negative consequences for the system in the form of higher system cost, GHG emissions and demand peaks.

6.1.3 Consumer costs

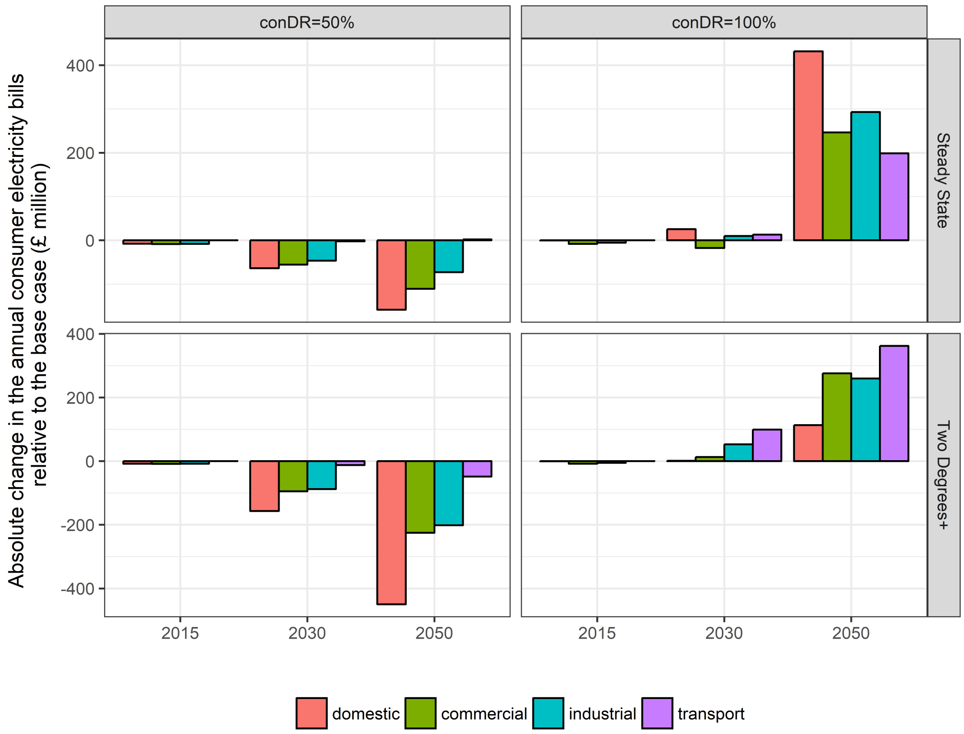
The impact of DSM on end-users is assessed by comparing their electricity bills with and without CON_CM. To remind the reader, consumer costs are calculated as the sum of the product of their hourly residual demand (without renewable generation) and real time price for electricity during the year. The calculation does not account for the retail uplift applied by utilities since the aim is to understand how different types of consumers contribute to the total cost of generating electricity at the system level.

Today most consumers buy electricity through a utility (or an aggregator in our case), which has access to the wholesale market. Only some large end-users (e.g. industry) can hold contracts directly with the generators. Therefore, it makes sense to bill consumers at a flat tariff (based on average daily or monthly cost of power purchased by the aggregator). However, seeing that consumers react to the RTP and thinking of the future expectations from the 'smart grid' to operate on the real time cost of generating electricity, the consequences of herding when consumers are billed at RTP are investigated. Accounting consumer costs at RTP also exaggerates the issue of cost allocation to different types of consumers and highlights the importance of appropriately structuring electricity tariffs in the context of DSM.

6.1.3.1 Analysis of different consumer sectors

We start by analysing the absolute change in the annual cost of power incurred by each economic sector (Figure 6.38).

Figure 6.12: Absolute change in the annual consumer electricity bills with CON_CM relative to the base case by sector, 2015-2050. Source: ESMA



In the Steady State scenario, it is the domestic sector which sees the highest savings across all years (i.e. at 50% participation level, conDR=50%), but also the highest losses in the case of herding (i.e. conDR=100%). In 2050 maximum savings by the domestic sector amount to £158 million per year, whereas maximum losses reach £431 million per year. This happens for two reasons. Firstly, domestic sector has the highest demand for electricity in the Steady State scenario. To compare, residential end-users consume 136.7TWh of electricity in 2050 compared to 101.2TWh by commercial, 72.7TWh by industrial and 15.5 TWh by transportation sectors (see Appendix F). Secondly, domestic sector is assumed to have more thermal flexibility as a result of a higher number of electric heating (EH) units installed[3]. The combination of these two factors means that DSM has a larger impact

[3]The number of TES units is calculated as half the number of EH units)

on the domestic consumer bills in the Steady State scenario, i.e. it leads to highest absolute savings when prices are reduced and the highest losses when the prices are high.

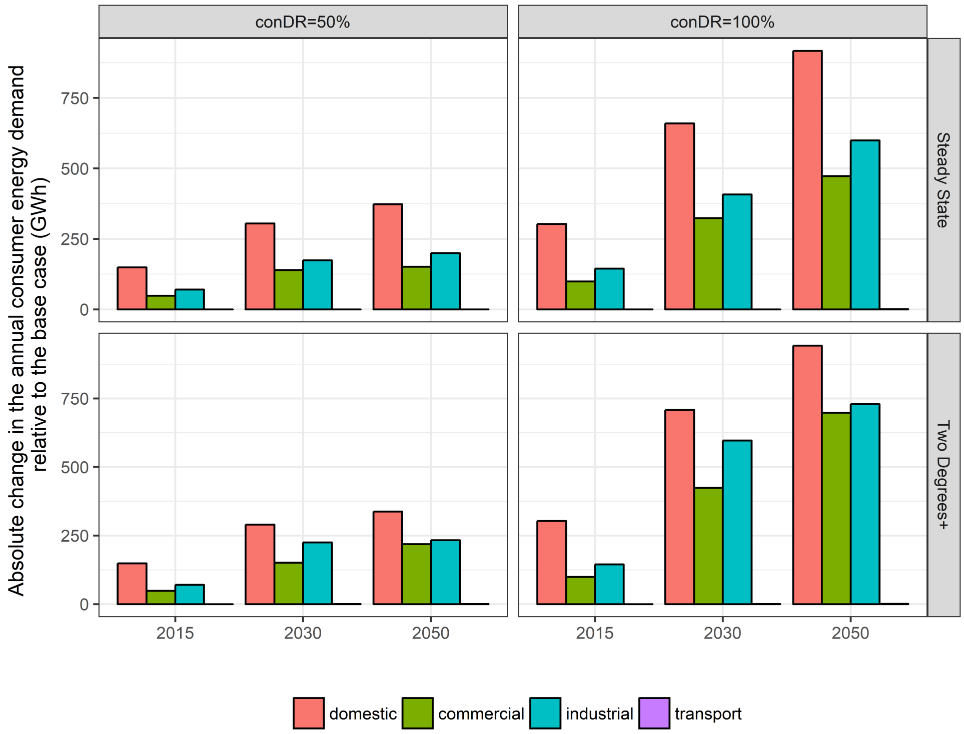
In the Two Degrees+ scenario, at 50% participation level (i.e. conDR=50%) residential sector sees much higher savings in 2050 (£450 million per year) compared to the Steady State scenario. When the market herds (i.e. conDR=100%) domestic consumers experience minimal losses (£113 million per year), whereas electric transportation pays an additional £362 million per year in 2050 (the highest absolute increase across all sectors). This occurs because the residential sector is assumed to have the highest share of solar capacity (25%) compared to non-domestic sectors (12.5% each), and so becomes less exposed to the wholesale electricity market in the Two Degrees+ scenario (especially in 2050 when renewable penetration level is at its highest)(see Section B.1). On the other hand, electric transportation witnesses higher demand for electricity in the Two Degrees+ (as a result of transport electrification) compared to the Steady State (35 TWh versus 15.5 TWh) and as a result experiences a significant increase in the annual bill.

Figure 6.13: Relative change in the annual consumer electricity bills with CON_CM (conDR=100%) relative to the base case by sector, 2015-2050.

Scenario	Year	Domestic	Commercial	Industrial	Transport
Base year	2015	0.0%	-0.2%	-0.1%	-0.7%
Steady State	2030	0.3%	-0.3%	0.2%	4.8%
	2050	3.6%	2.8%	4.7%	16.6%
Two Degrees+	2030	0.0%	0.2%	0.9%	8.7%
	2050	1.2%	3.4%	3.6%	16.5%

In relative terms it is the transportation sector that ends up paying the price for herding seeing an almost 17% increase in the annual electricity bill in 2050 in both scenarios (Figure 6.40). The first reason for these observations is that electric transportation constitutes the most flexible consumer since it essentially represents one large electrical store. In addition to this, transportation does not experience a change in the amount of energy consumed when DSM is deployed since electric vehicles operate with the same level of losses in the base case (Figure 6.14).

Figure 6.14: Absolute change in the annual consumer energy demand with CON_CM relative to the base case by sector, 2015-2050.



In contrast, the residential sector experiences the highest increase in demand for electricity (Figure 6.14), which explains how largest absolute losses in the Steady State scenario are reduced in relative terms (calculated by dividing absolute losses by the demand increase). The non-domestic sectors see relatively similar impacts from DSM due to their likeness in the level and daily pattern of electricity demand. In relative terms, out of all stationary consumers it is the industrial sector which experiences the larger losses. In 2050, non-domestic bills go up by a few percent in the Steady State and Two Degrees+ scenarios.

In Figures 6.15 and 6.39 we look closer at the impact of DSM on consumer demand profiles in the case of the market herding (conDR=100%). In the Steady State scenario it is possible to see that the domestic demand for electricity is higher and more correlated with the price curve when compared to the other sectors, which leads to higher level of losses experienced by the sector (Figure 6.15). For the Two Degrees+ case, although the domestic sector contributes to the price peaks, its residual load curve (calculated as the difference between demand and renewable generation) dips during the day due to more solar generation, leading to a reduction in the exposure of the sector to the electricity market risk (Figure 6.39). Electric transportation (being the most flexible sector) changes its demand curve from an almost flat to a very variable profile that is highly correlated with the electricity price curve, which leads to the highest relative losses in the case of herding for both scenarios.

Figure 6.15: Consumer demand profiles with and without CON_CM (conDR=100%) by sector, 16 November 2050 (Steady State). Source: ESMA

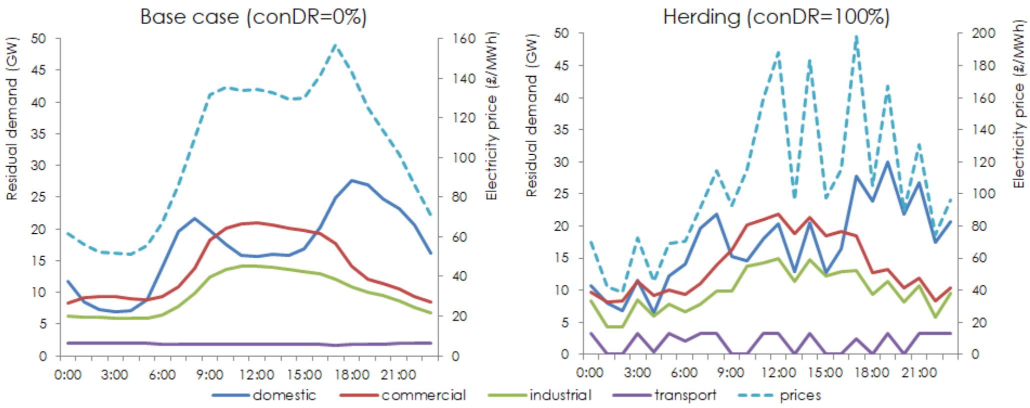
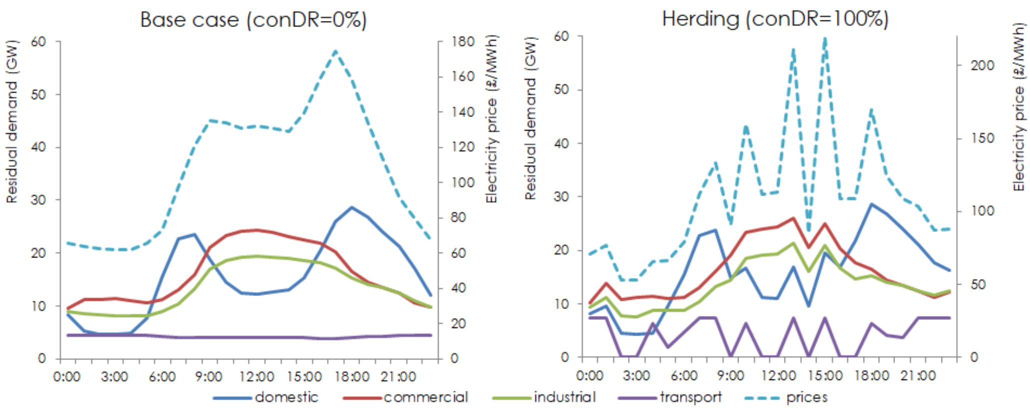


Figure 6.16: Consumer demand profiles with and without CON_CM (conDR=100%) by sector, 16 November 2050 (Two Degrees+).



6.1.3.2 Analysis of different consumer types

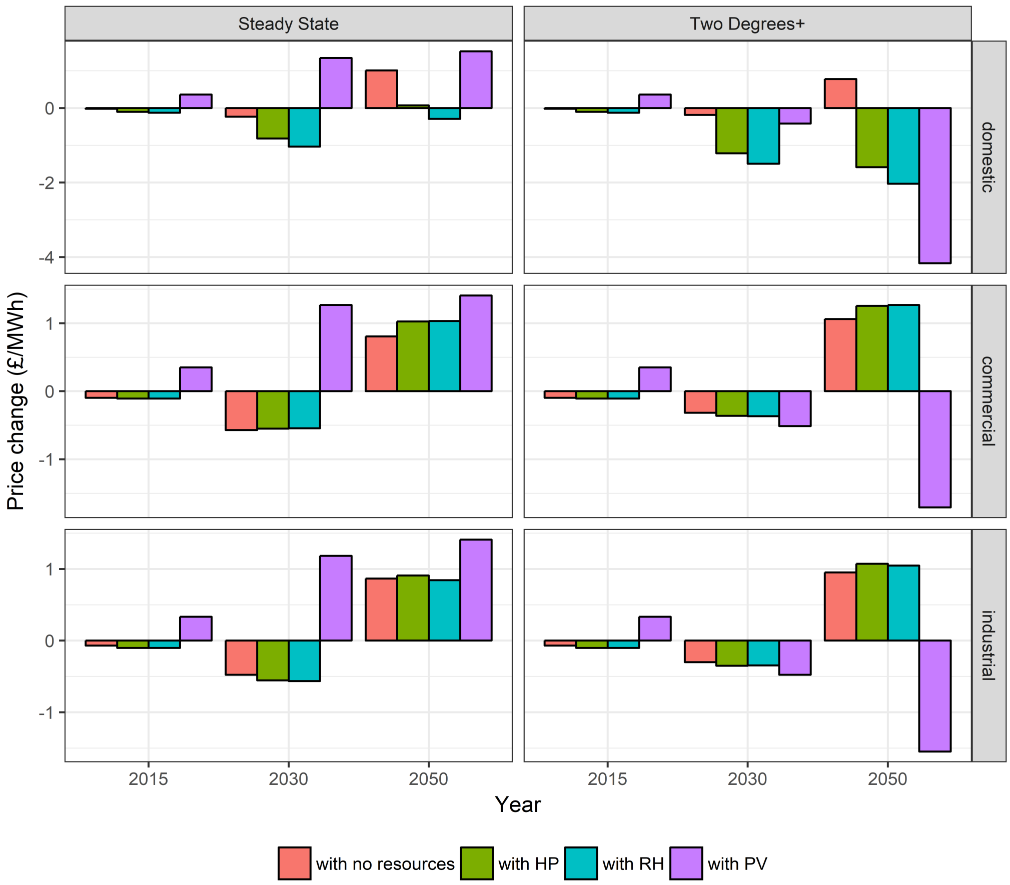
It is of interest to look at how DSM impacts consumers of different types. We consider 31 different consumer agents depending on the combination of resources available to consumer (i.e. HP, RH, TES, PV, and ES) and his economic sector (i.e.

domestic, commercial, industrial, and transport).

Since end-users of each type vary significantly in terms of size and resource capacity, instead of looking at the absolute change in the annual electricity bill we analyse the change in the average cost per unit of energy purchased over the year (or the average price for electricity). Hence the impact of DSM is assessed by comparing the price of electricity under CON_CM to the base case (when consumers are passive). The aim of this analysis is to investigate how DSM impacts inflexible as well as flexible consumers, since the former are price takers whereas the latter are price makers.

Figure 6.41 demonstrates how the price for electricity changes for consumers without flexible resources in the case when all consumer cost minimise by deploying CON_CM regime (conDR=100%).

Figure 6.17: Change in the annual electricity price for inflexible consumers with CON_CM (conDR=100%) relative to the base case by type, 2015-2050. Source: ESMA.

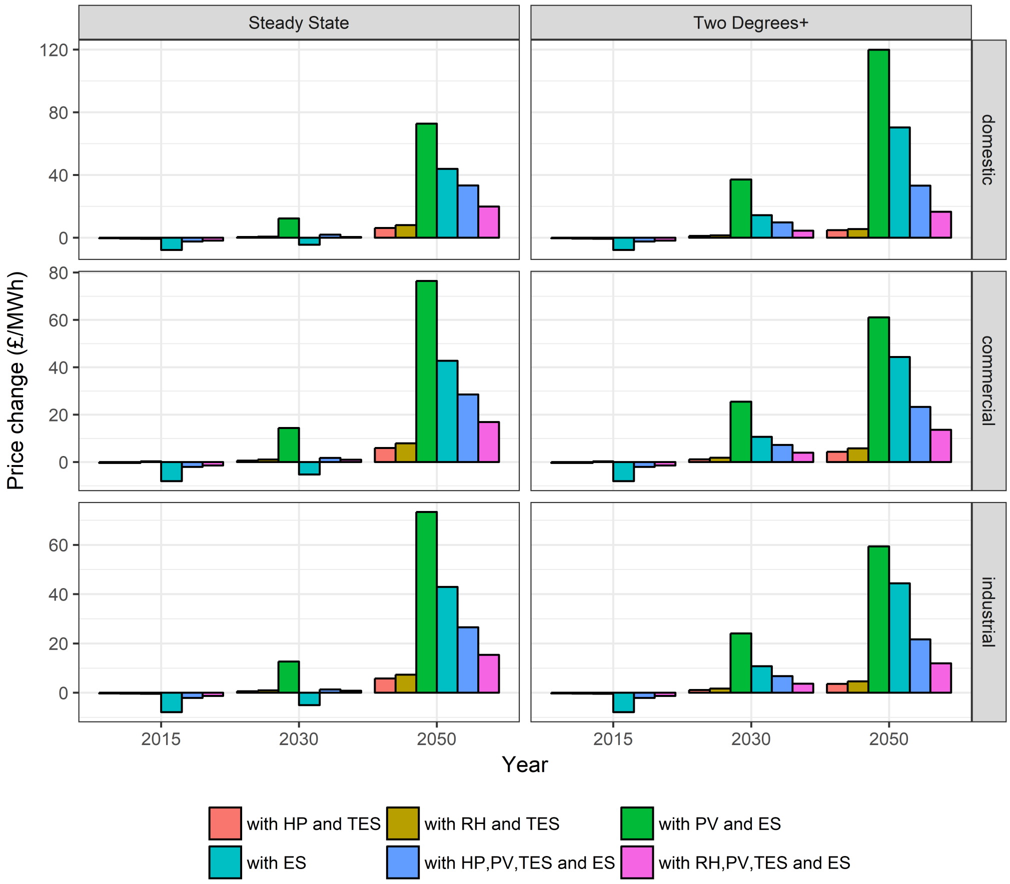


It is evident that in the Two Degrees+ scenario consumers with PV benefit the most from DSM with the domestic sector making the largest saving (-£4/MWh). This happens because when the market herds, inflexible consumers with solar PV are unable to shift demand or increase self-utilisation of solar power. Consequently, these consumers end up selling the surplus generation at the higher price, whereas the power they do purchase comes at a lower rate since after coordination demand and price peaks shift to new time periods. The domestic consumers benefit the most from this situation because their level of demand is less correlated with the solar generation profile allowing them to export more during the day at high prices. Non-domestic consumers with solar PV have a higher level of self-consumption during the day and hence a lower level of export.

We note that this is not the situation in the Steady State scenario where consumers with PV see an increase of around £1/MWh in 2030 and 2050. This is because in the Steady State scenario electricity prices are on the whole higher (due to a lower renewables capacity). Hence, the cost of purchased electricity is not covered by consumer profits from exporting renewable generation. With the exception of domestic end-users, the remaining non-flexible consumers see a reduction in the average price level up until 2030 and an increase in 2050 for both Two Degrees+ and Steady State scenarios. Domestic consumers with electric heating (i.e. with HP and RH) do not see significant price increases in 2050 due to their demand profile being less correlated with the price curve during herding.

In contrast to non-flexible consumers, flexible consumers see their average electricity price increase as a result of the market herding (Figures 6.44 and 6.46). Consumers of type 7 (with PV and ES) lose out the most paying at additional £60-120 per MWh across the two national scenarios. In contrast to non-flexible consumers with solar PV, those with PV and ES are able to herd towards periods of high electricity prices. Consequently, they reduce self-utilisation in hope of making a profit from the sale of electricity and end up purchasing power at the highest rates whilst selling at the lowest. The biggest change is observed for domestic consumers with ES and PV in the Two Degrees+ scenario. If in the base case they make

Figure 6.18: Change in the annual electricity price for flexible consumers with CON_CM (conDR=100%) relative to the base case by type, 2015-2050. Source: ESMA.

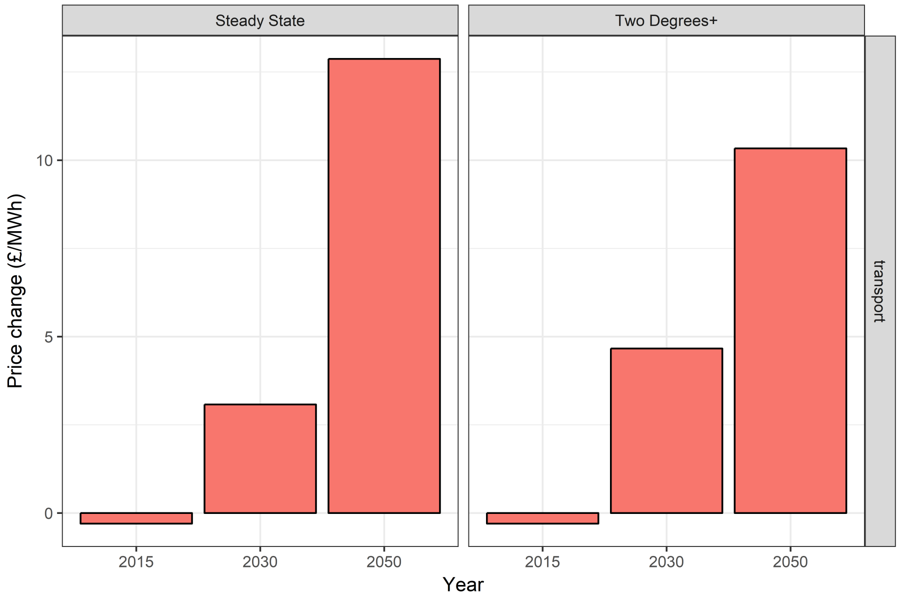


£44/MWh in the case of herding they end up paying £76 per MWh in 2050.

From analysing the flexible consumer costs we observe that the negative impact from herding is reduced as the level of non-deferrable load increases whilst the flexibility level decreases. For this reason consumers with electric heating (HP and RH) and storage (TES and ES) see smaller losses compared to consumers with just electrical stores. When comparing consumers with the same stores but different types of electric heating (i.e. RH with TES and HP with TES), we observe that consumers with heat pumps (HP) experience higher losses compared to consumers with resistance heating (RH). This is because the efficiency of a HP is higher compared to RH meaning that the non-flexible load is lower whilst the storage capacity is the same.

Finally, we note that consumers with just the electrical stores (including elec-

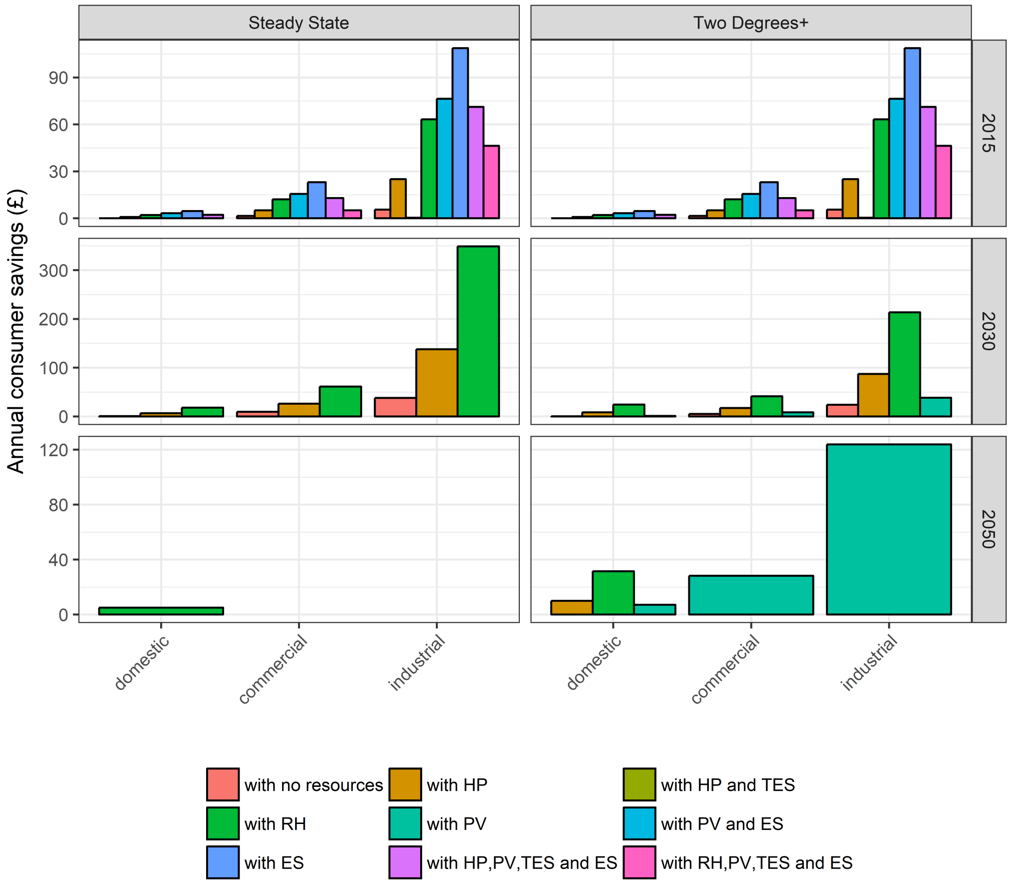
Figure 6.19: Change in the annual electricity price for electric vehicles with CON_CM (conDR=100%) relative to the base case, 2015-2050. Source: ESMA.



tric vehicles Figure 6.46) see a reduction in the cost of electricity in the earlier years which suggests that these consumers might adopt the cost minimisation strategy in the nearby future. However, once total market flexibility becomes high enough, herding harms these consumers the most. Compared to stationary consumers with ES, electric vehicles see a lower increase in the price level (£10-12 per MWh) in the case of herding. This comes as a result of limited charging capacity since EVs are only allowed to shift the charging pattern and not to discharge into the grid.

Figure 6.20 shows only those consumers who make savings during coordination with CON_CM with maximum participation rate (conDR=100%). We can see that in 2015 almost all consumers profit from DSM, with the more flexible consumers making the highest savings. However by 2030 only non-flexible consumers benefit in the case of herding under CON_CM. This is in line with one's expectations since non-flexible consumers are unable to shift demand and are therefore spared of paying the high rates. In 2050 only inflexible consumers with PV benefit from DSM. The fact that certain users benefits from herding when the system losses out, highlights the potential for a conflict of interest between consumers and the system. Moreover, if certain end-users benefit from a cost minimising strategy in the earlier years (e.g. those with ES), they are likely to continue with it in the future. Yet, at a certain point consumer herding can be harmful to the system and flexible consumers can end up suffering as a result of not adjusting to the new prices fast enough. In the worst case, the market becomes chaotic and the System Operator will have to interfere in balancing the grid, which can become expensive.

Figure 6.20: Annual consumer savings with CON_CM (conDR=100%) by type, 2015-2050. Source: ESMA.



6.1.4 Sensitivity Analysis

It is noted that the behaviour described in this section is extreme and assumes the presence of a smart home management device which will be able to perform the scheduling. For one, it is likely that consumers (especially domestic) will not expect the same rate for importing electricity as for exporting it, since the aggregator will take a share of the profits in return for the access to the wholesale electricity market. It is also a case that the System Operator is likely to make demand predictions taking into account long-term (years and months) as well as short term demand patterns. However, since the simulation is run with a gap of 15 years it was impossible to simulate this behaviour.

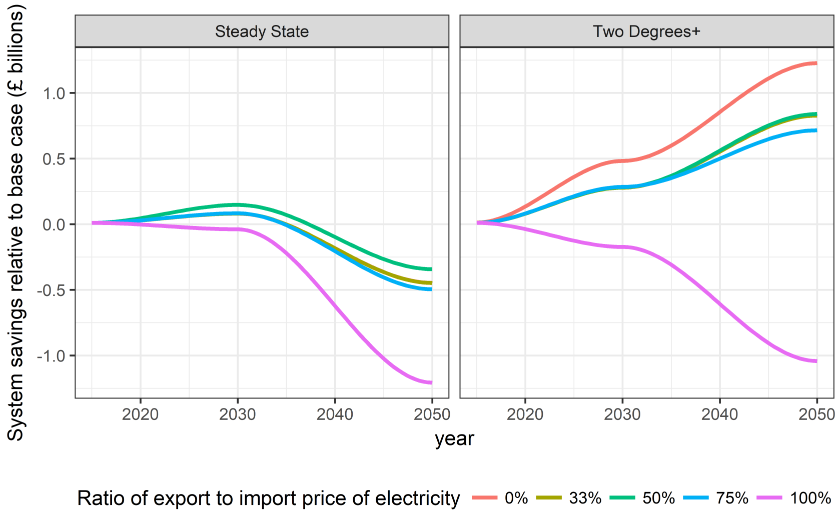
In this subsection we explore how model parameters assumed for ESMA (including export price, weight to past demand, and consumer storage capacity) affect the system during DSM implementation and offer explanation and significance of the observations.

6.1.4.1 Expected consumer export price

Figure 6.21 demonstrates system savings at different levels of the export price (calculated as the percentage of the import price). It is possible to see that the herding effect is reduced as the price for exporting electricity is lowered, as indicated by the increasing level of savings. This happens because consumers see less benefit in selling electricity and prioritise self-consumption. As a result, the system experiences a smoother and more predictable demand pattern allowing it to utilise renewable resources and storage more effectively. When the export price is zero, in the Steady State the system starts to see losses post 2035, whereas in the Two Degrees+ scenario the savings are positive reaching £1.2 billion per year in 2050.

Interestingly in the Steady State scenario savings are highest when the export price is half the import price, but then go down when the export price drops to 33% and 75% of the import price, indicating a non-linear relationship between the export price and system cost. This happens because low export prices deters consumers from exporting electricity, therefore limiting the amount of renewable energy available at the system level. Setting the export price too high leads to an elevated total

Figure 6.21: Annual system savings with CON_CM (conDR=100%) with varying export prices. Source: ESMA.



system demand as consumers operate more storage in order to export power in hope of making a profit. The amount of consumer export then becomes too high and the system fails to absorb it all, resulting in the curtailment of transmission level renewable generation. Hence, there is an optimal export price at which consumers are willing to export electricity without causing chaotic demand.

In the Two Degrees+ scenario there is an abundance of renewable generation at the transmission level, hence consumer exports are not needed for which reason the case when the export price is set to zero achieves the highest savings. In contrast in the Steady State scenario there are less transmission level renewables, therefore the 50% export to import price ratio works best by incentivising some consumer export into the system.

6.1.4.2 Demand predictions

Another important parameter in the model is w, which determines the weight to previous electricity demand in the system. The reader is reminded that the System Operator uses w during the step of predicting day-ahead system demand $L^*(t,d)$ according to the following formula as described in Section 3.4.4:

$$L^*(t,d) = w \cdot L_{agg}(t,d) + (1-w) \cdot L(t,d-1), \tag{6.1}$$

where,

$L(t, d-1)$ is the system demand outturn in the previous day,

L_{agg} is the system demand predicted by the aggregators, and

$w \in [0,1]$ represents the weighing parameter to demand in the previous year.

When $w = 0$, the SO places no weight to past demand and only acts on the current information received from the aggregators. In contrast when $w = 1$, the SO is only guided by yesterday's demand. In order to investigate the sensitivity of the model to w, we observe the parameter for extreme settings, i.e. $w = \{0,1\}$, and observe total system cost when all consumers cost minimise in 2015, 2030 and 2050 in the Two Degrees+ and Steady State scenarios. The analysis is carried out for 100% participation level only, since it was demonstrated to lead to the highest level of herding.

Figure 6.22: Annual system cost with varying weight to past prices with and without CON_CM (conDR=100%), 2015-2050. Source: ESMA.

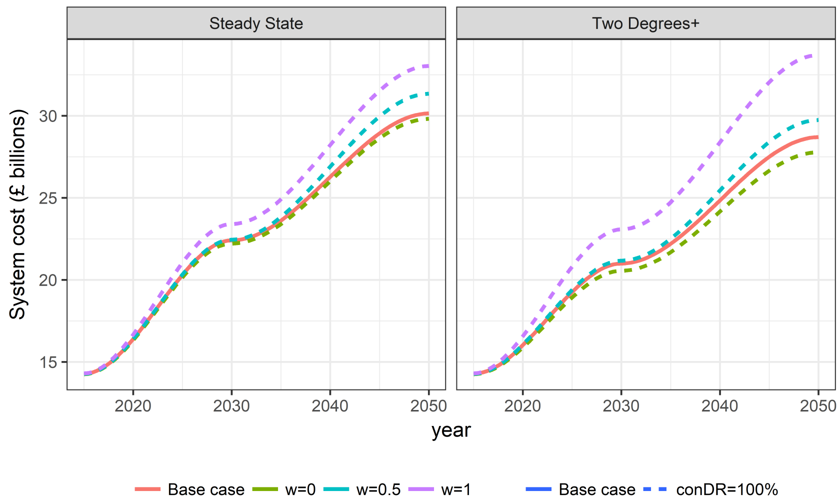
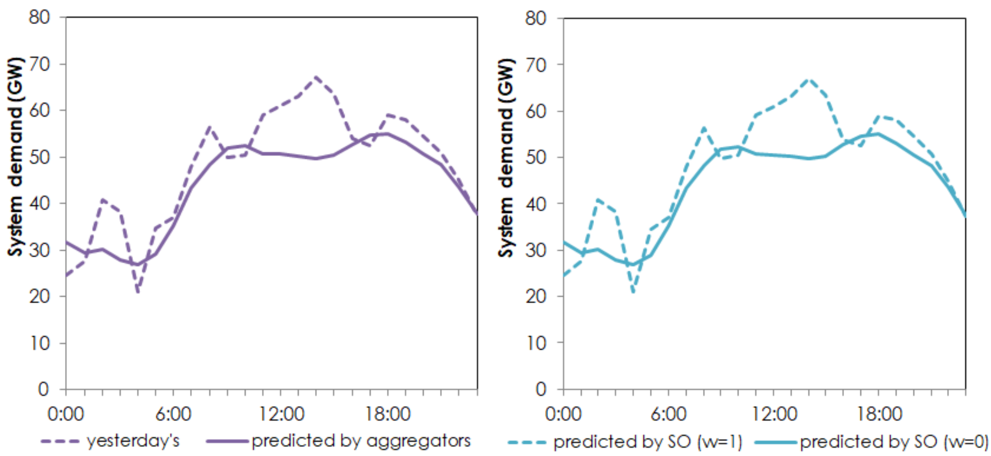


Figure 6.22 shows the variation in system cost with different settings for w. From the figure, it is possible to see that the lowest system cost is achieved when $w = 0$, corresponding to the case when the SO does not take past demand into account at all. In fact, the system experiences savings even when all consumers cost minimise (a case which lead to losses in the default scenario, i.e. $w = 0.5$). The highest system cost is achieved when $w = 1$, corresponding to the case when

the SO predicts day-ahead demand based only on yesterday's demand information. The middle case ($w = 0.5$) is the default setting and takes the average of past prices and those predicted by the aggregators.

Figure 6.23 demonstrate how the System Operator makes a prediction for the day-ahead system demand. The left chart shows the demand information obtained by the SO: that from the day before (dashed line) and that received from the aggregator (solid line). Chart on the right side, shows the demand profile predicted by the SO. When $w = 0$ (solid line) the SO bases the prediction on the information provided by the aggregators only, which is identical to the profile in the left chart identified by the solid line. When $w = 1$ the SO predicts day-ahead demand predictions basing it only on yesterday's demand outturn (dashed line). Naturally, when $w = 0.5$ the predicted demand profile is calculated as the average between the two.

Figure 6.23: Demonstration of how the SO makes a prediction for day-ahead demand with CON_CM (conDR=100%), 2050 (Two Degrees+). Source: ESMA.



Figures 6.24 - 6.27 demonstrate how the prediction process impact the system when performed during a few consecutive days. When $w = 0$, the demand and price profiles predicted by the SO remain fairly smooth as the SO ignores past data (Figures 6.24 and Figure 6.25). On receiving the predicted prices, consumers schedule their resources to periods of low electricity prices as indicated by the green solid line in Figure 6.24. This leads to the creation of new demand peaks. However, the peaks always happen around the same periods since the price information sent by the SO always has the same pattern. Hence, herding is limited by the consumer's capacity

in being able to fill the valleys of the system's non-deferrable demand (00:00-6:00).

Figure 6.24: Predicted and on-the-day system demand outturn with CON_CM (conDR=100%, w=0), 2-4 January 2050 (Two Degrees+). Source: ESMA.

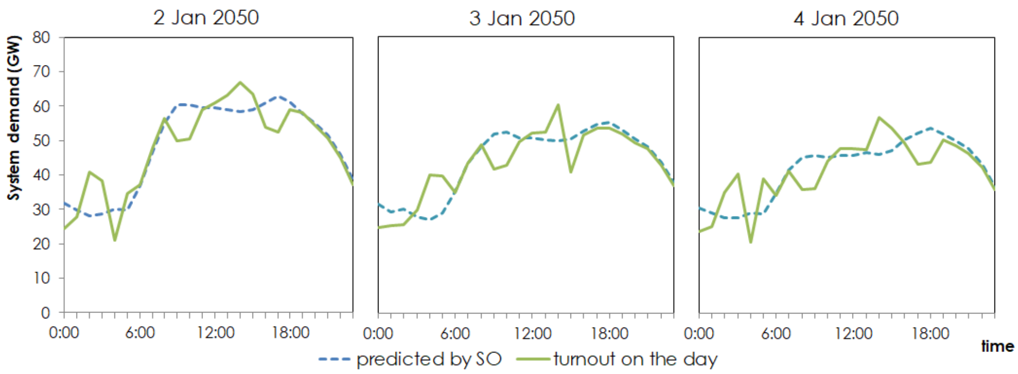
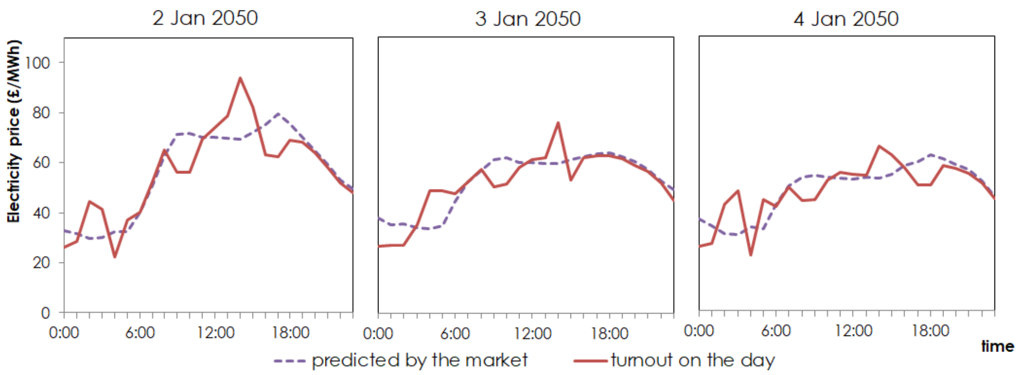


Figure 6.25: Predicted and on-the-day wholesale electricity prices with CON_CM (conDR=100%, w=0), 2-4 January 2050 (Two Degrees+). Source: ESMA.



In the case when the SO bases day-ahead predictions solely on the past data (i.e. when $w = 1$), the daily system demand pattern shifts from day to day, i.e. peaks on the 2nd of January turn into valleys on the 3rd of January and so on (Figure 6.26). The daily prices shift together with the demand profile, which leads to situations where consumers schedule flexible demand to already existing non-deferrable demand peaks (Figure 6.27). Hence the daily demand and price profiles end up being much more volatile compared to the case when $w = 0$. This leads to increased system costs as a result of suboptimal utilisation of renewable generation at the transmission level and increased ramping of dispatchable generators.

Figure 6.26: Predicted and on-the-day system demand outturn with CON_CM (conDR=100%, w=1), 2-4 January 2050 (Two Degrees+). Source: ESMA.

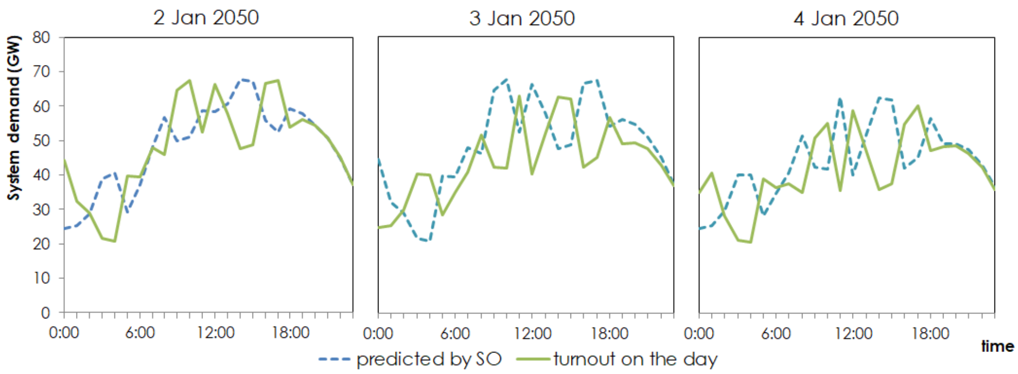
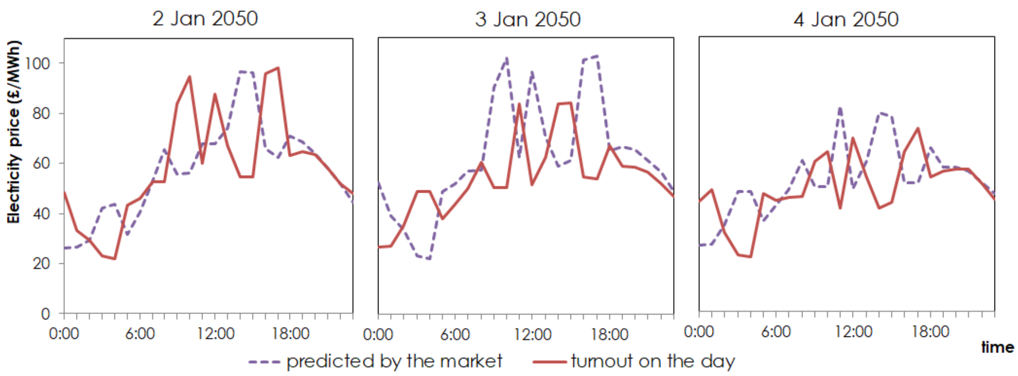


Figure 6.27: Predicted and on-the-day wholesale electricity prices with CON_CM (conDR=100%, w=1), 2-4 January 2050 (Two Degrees+). Source: ESMA.



6.1.4.3 Consumer storage capacity

Finally, we investigate the sensitivity of the system to consumer storage capacity by changing this parameter by 25% around the default setting. The sensitivity is measured by tracking annual system cost and greenhouse gas (GHG) emissions as well as consumer bills in 2050 (Two Degrees+).We consider the case when 100% of consumers deploy CON_CM (i.e. cost minimising based on RTP) since it renders the most extreme case of herding allowing us to observe the changes more clearly.

From Figure 6.28 we can see that increasing consumer storage capacity leads to higher system cost and the level of GHG emissions, as consumers have more capacity to shift demand and herd. As we have seen earlier this leads to higher demand peaks and more volatile and elevated prices. It is noted that the system is marginally more sensitive towards domestic rather than non-domestic storage. This happens because domestic storage is smaller in size compared to commercial and industrial users. This comes as a result of a higher number of heat pumps (HP) and thermal storage (TES) assumed in the domestic compared to non-domestic sectors, which allows more domestic consumers to shift thermal demand. To elaborate, in the Two Degrees+ (2050) scenario almost all domestic consumers have a HP and half of them have a TES. This means that when the number of electrical stores is added in the sector it is almost certain that it will be added to an end-user with a HP or to a consumer with a HP and a TES. Consequently, domestic consumers utilise ES in combination with HP (and TES) which allows them to shift thermal as well as non-thermal demand. In the non-domestic sectors it is more likely that an ES unit will be added to an end-user without any thermal resources and so the impact is lower. The observations of the annual level of GHGs are very similar to those of system cost.

Figure 6.28: Sensitivity of system costs and GHG emissions to installed consumer storage capacity with CON_CM (conDR=100%), 2050 (Two Degrees+). Source: ESMA.

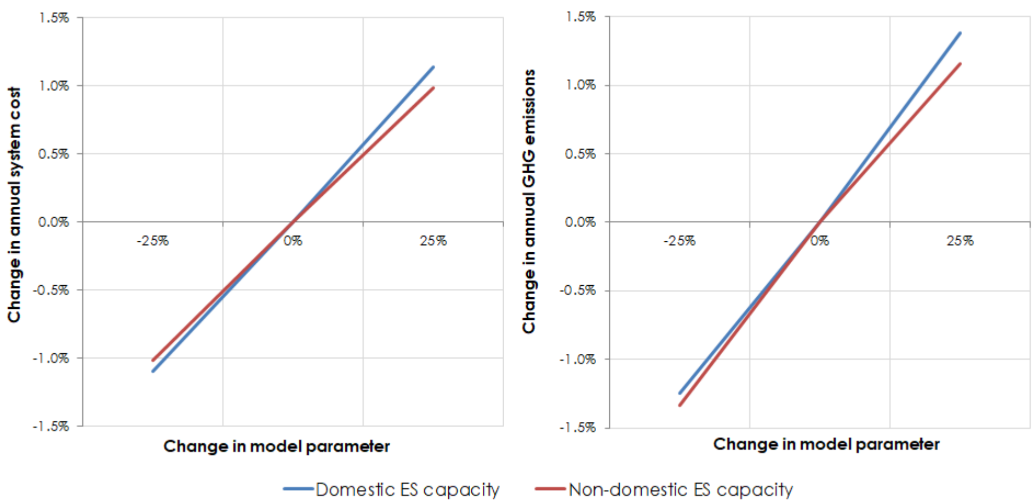
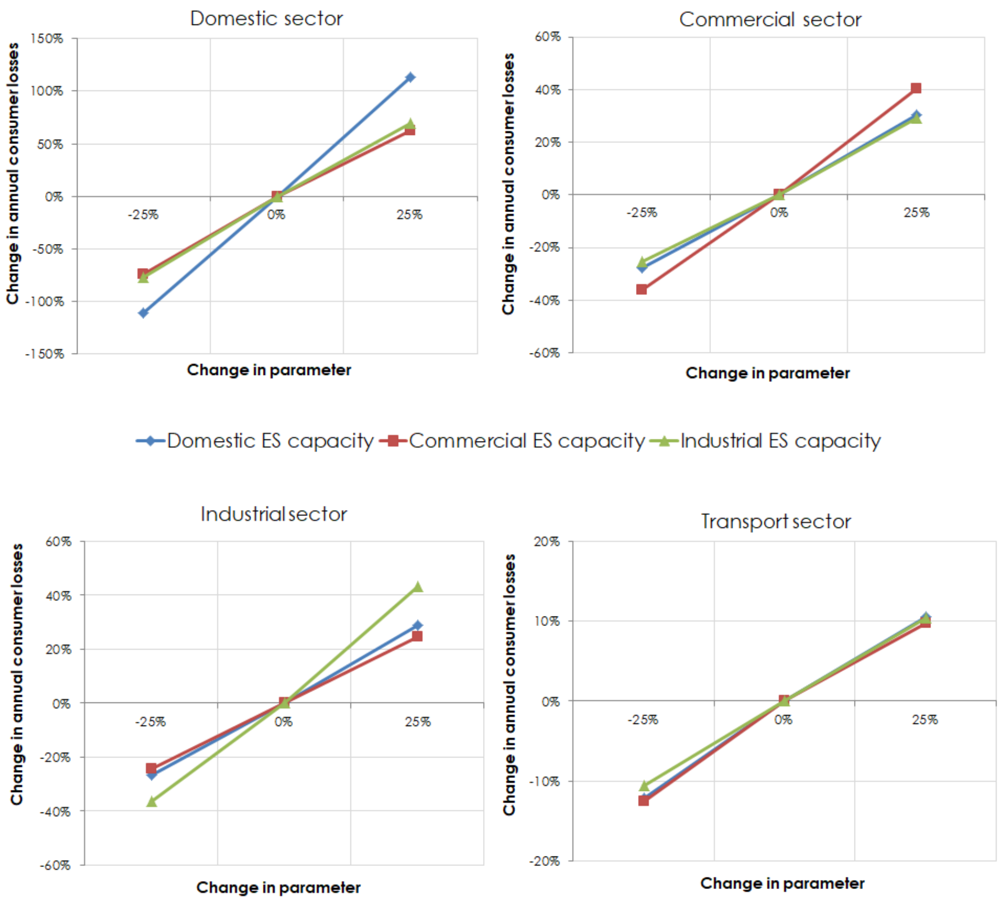


Figure 6.29 demonstrates how changing consumer storage capacity affects consumer losses as a result of herding under CON_CM. Losses are calculated by taking the difference between consumer annual bill under CON_CM and the base case (when consumers are passive). Different colours indicate the parameter be-

ing changed, whereas different charts indicate the sector under consideration. As can be expected consumer losses increase as their storage capacity increases, which is in-line with the earlier observations of system cost. In fact consumers across all stationary sectors are most sensitive to the changes in their own storage capacity, especially the domestic sector. This is because higher storage capacity enables consumers to herd more towards expensive time periods compared to their peers. Electric transportation is almost equally sensitive to the changes in electric storage capacity across all stationary sectors.

Figure 6.29: Sensitivity analysis of annual losses incurred by different sectors to installed storage capacity with CON_CM (conDR=100%), 2050 (Steady State). Source: ESMA.



6.1.5 Conclusion of part I

In the first section of the results chapter, we investigated the simplest form of demand side management CON_CM, whereby consumers scheduled demand based solely on the predicted real-time price for electricity. We considered three snapshot years (2015, 2030, 2050) for two national scenarios (Steady State and Two Degrees+), where the impact of demand side management was assessed in terms of system costs, GHG emission levels and system demand peaks as well consumer electricity bills at different consumer participation level.

It was demonstrated that cost minimisation by consumers based on RTP, can be beneficial to the system in the short term when consumer flexibility or consumer participation in DSM is low. However, as the proliferation of flexible consumer resources increases so do the risks of herding and chaotic market behaviour as consumers try to adjust to daily wholesale prices. According to the simulation, consumers tend to benefit together with the system, however inflexible consumers are able to save when the market herds. This is a point of concern since it is possible to imagine that consumers will follow their own selfish objectives, which can result in compromising on the system values. The simulation has shown that flexible consumers end up being more vulnerable to market prices since they have the capacity to herd towards expensive time periods. Such outcome may deter consumers from investing into flexible technology, which is counterproductive to the government goals on engaging consumers and increasing system flexibility.

From performing the sensitivity analysis it was possible to show how the price of consumer exports can serve as a tool to control herding. However, it is also a case that by limiting exports of renewable energy generated by consumers the availability of renewable energy at the system level is reduced. Another tool for controlling herding is stabilising the predicted electricity prices which are sent into the market, as has been demonstrated during the sensitivity analysis of the system to parameter w (the weight to past demand used by the SO).

Of course, the scenarios discussed in this section are exaggerated and it is likely that the System Operator would intervene before extreme events would occur.

However, such interventions could cost the system and consumers dearly, and so it is important to consider ways to avoid such negative consequences on the system before they occur.

In the next section we discuss the role of aggregators in managing consumer coordination and the benefits and risks it might bring to the system.

6.2 Part II: The benefits and risks of aggregator-led demand DSM

In the second section of the results, we explore the role of the aggregators in balancing the future electricity system. The reader is reminded that in the context of this model an aggregator agent represents any entity which can pool consumers together and act as a middle man between end-users and the wholesale market. Hence, an aggregator can represent a utility retailing electricity to consumers, or an online platform which coordinates their demand and generation. The reason for such representation is that the boundary between a traditional utility (whose sole responsibility is to retail wholesale electricity to end-users) and a traditional aggregator (whose responsibility is to perform demand side management) is becoming blurred. For example, it is now possible to be an electric utility through an online platform and pool smaller consumers together to access wholesale markets without necessarily being a large company.

We begin by investigating the benefits aggregators can bring to the system by means of deploying algorithm AGG_DF, which has been adapted from (Gan et al., 2013). In the algorithm, an aggregator uses total consumer residual demand as a proxy for price and negotiates the demand with consumers over a number of iterations until the system converges. The result of such coordination is a peak reducing demand side response. The upside of AGG_DF is its simplicity in overcoming consumer herding since it does not use system prices. However, its downside is the fact that it does not take into generation from renewables at the transmission level.

In the second part of this section, we investigate potential issues which may arise as a result of aggregators utilising DSM for the purpose of competing in the wholesale and retail markets. This is demonstrated by deploying algorithm AGG_CM (developed from AGG_DF), which is used by an aggregator to actively minimise the cost of purchased power. Conditions are identified where aggregator participation in AGG_CM becomes harmful to the system, as they instruct consumers to shift demand towards the same periods of low electricity prices (similarly to consumer herding described in Section 6). We then explore the implications of consumers being able to switch aggregators and demonstrate that retail competition can aggravate the negative consequences of herding and lead to higher system costs.

Finally, algorithm SO_CM (extended from AGG_CM) is deployed as a tool for overcoming aggregator and consumer herding. In SO_CM, the System Operator communicates with the market and the aggregators, thereby monitoring system cost during demand side coordination. The superiority of algorithm SO_CM to AGG_DF is demonstrated highlighting the importance of considering the system as a whole when deploying DSM. This section is concluded by analysing how retail tariff structure and storage capacity can affect consumer savings from DSM.

6.2.1 The value of aggregators in balancing the grid

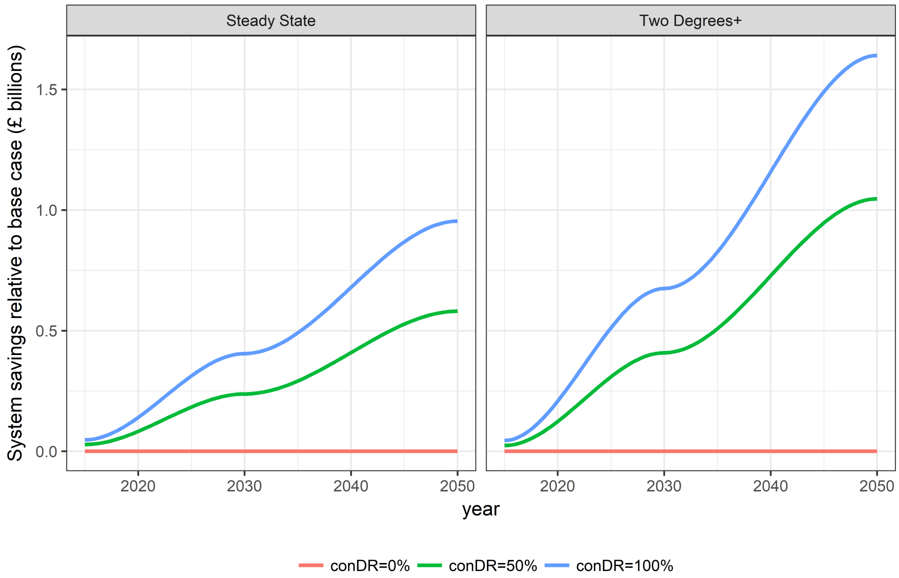
6.2.1.1 System cost, demand and GHG emissions

Figure 6.30 shows the range of system savings achievable with AGG_DF as more consumers participate in DSM in the Steady State and Two Degrees+ scenarios. It is clear that the system benefits from having more consumers participate in DSM. Maximum system savings are noticeably higher under Two Degree+ amounting to £1.64 billion a year in 2050 due to a higher degree of consumer flexibility assumed for this scenario. It is noted that inflation is not accounted for during the calculation of wholesale prices.

These savings come as a result of lower and less volatile electricity prices (Figure 6.31). As can be seen from the figure and the table underneath, mean electricity prices and their volatility consistently drop during the years as result of deploying AGG_DF. Across the two scenarios, the change is more notable for the Two Degrees+ case, which can be explained by the higher capacity of variable renewables and consumer flexibility. In 2050 the mean electricity price drops by as much as 9.2%, whereas annual price volatility decreases by 15% relative to the base case (when all stakeholders are passive).

We note that that system savings level out between 2030 and 2035 which coincides with increased renewable capacity in the Steady State scenario (Figure 6.32) and a reduction in the number of resistance heaters (Figure 6.33). Both situations lead to a decrease in the steepness of the wholesale electricity price curve and con-

Figure 6.30: Annual system savings achieved with AGG_DF relative to the base case, 2015-2050. Source: ESMA

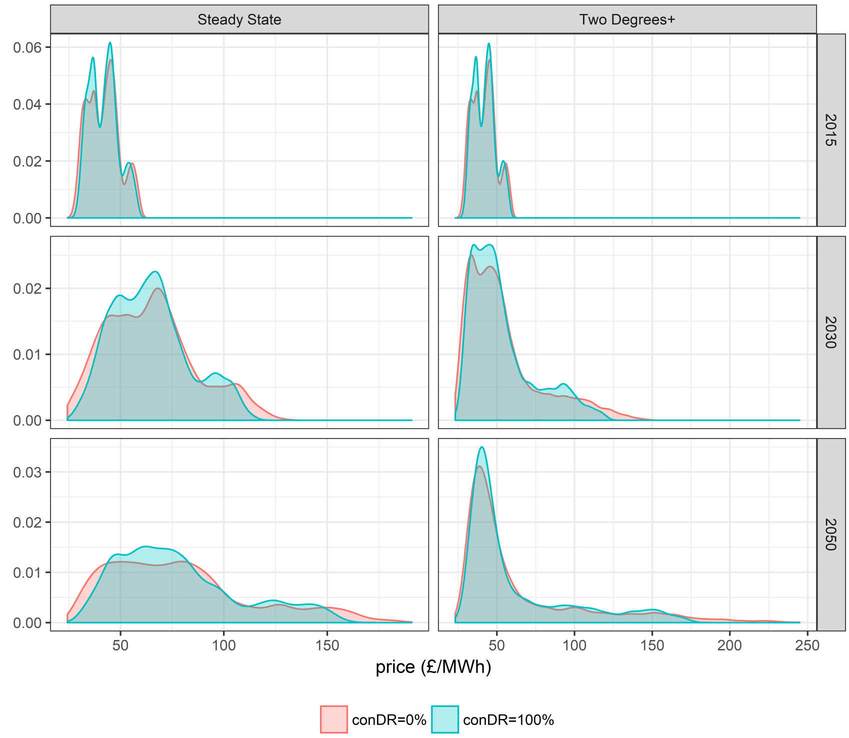


sequently a reduction in the marginal benefit of DSM.

In terms of reducing greenhouse gas (GHG) emissions, the system starts to benefit by 2030 in the Two Degrees+ scenario and only marginally by 2050 in the Steady State scenario (Figure 6.34). The reductions in the level of GHGs are relatively small because when DSM is deployed the system utilises consumer storage (which is not 100% efficient). This leads to loses and so the total electricity consumption goes up relative to the base case. This observation also highlights the limitations of ESMA, which assumes the same efficiency of generators throughout their operational lifecycle. In reality, the efficiency of thermal generators changes depending on their ramping rate, and so when they run smoother the efficiency is higher meaning that less fuel is needed compared to the case when they have to constantly cycle. In addition to this, ESMA does not penalise generators for rescheduling, nor does it impose a cost on the curtailment of renewables. Nevertheless, it is possible to see that environmental benefits are much more significant in the Two Degrees+ scenario where the capacity of variable renewables is much larger.

Figure 6.35 shows the impact of deploying AGG_DF on the annual system demand peak in the Steady State and Two Degrees+ scenarios. For the Two Degrees+

Figure 6.31: Wholesale electricity prices with and without AGG_DF, 2015-2050. Source: ESMA



Statistic	DSM / Year	Steady State: Base case (conDR=0%)	Steady State: AGG_DF (conDR=100%)	Steady State: % change	Two Degrees+: Base case (conDR=0%)	Two Degrees+: AGG_DF (conDR=100%)	Two Degrees+: % change
Mean (£/MWh)	2015	43.9	43.7	-0.5%	43.9	43.7	-0.5%
	2030	70.6	69.1	-2.2%	60.8	58.7	-3.5%
	2050	88.2	85.1	-3.5%	76.6	72.0	-6.0%
SD (£/MWh)	2015	7.7	7.0	-9.3%	7.7	7.0	-9.2%
	2030	21.6	18.7	-13.6%	24.2	20.9	-13.5%
	2050	34.7	29.7	-14.4%	41.4	35.2	-15.0%

case, the reductions are higher reaching 5.4GW and 7.5GW in 2030 and 2050 respectively, which is in-line with higher consumer flexibility and the level of heating and transport electrification assumed for this scenario. Higher consumer participation rate has a positive impact on the system resulting in a lower system demand peak, which is in agreement with the earlier observations regarding system savings achievable with AGG_DF.

Figure 6.36 shows the change in the annual generation mix as a result of deploying AGG_DF relative to the base case in 2030 and 2050 for the two national scenarios. We note that the use of pumped storage and 'other_therm' (mainly OCGT, diesel and fuel oil) goes down in all four cases demonstrated in the chart, which is offset by increased utilisation of gas (under Steady state) and dispatchable renew-

Figure 6.32: Installed renewable capacity in the Steady State scenario, 2015-2050. Source: National Grid (National Grid, 2017a)

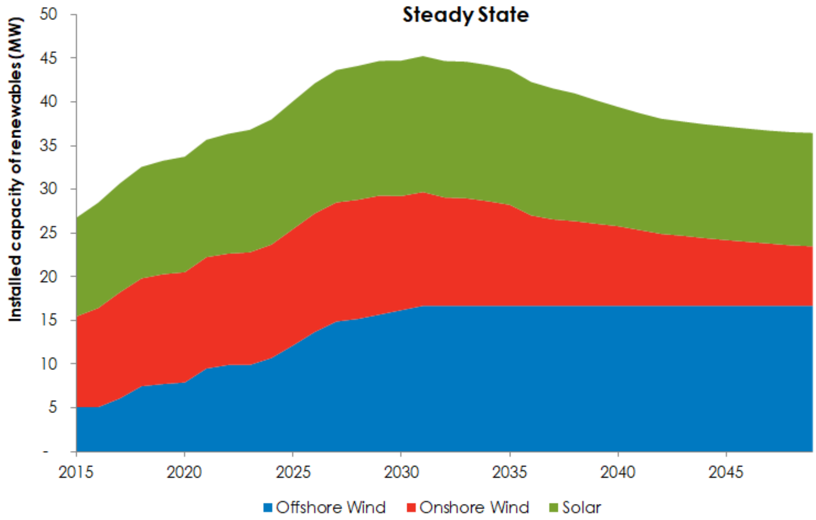
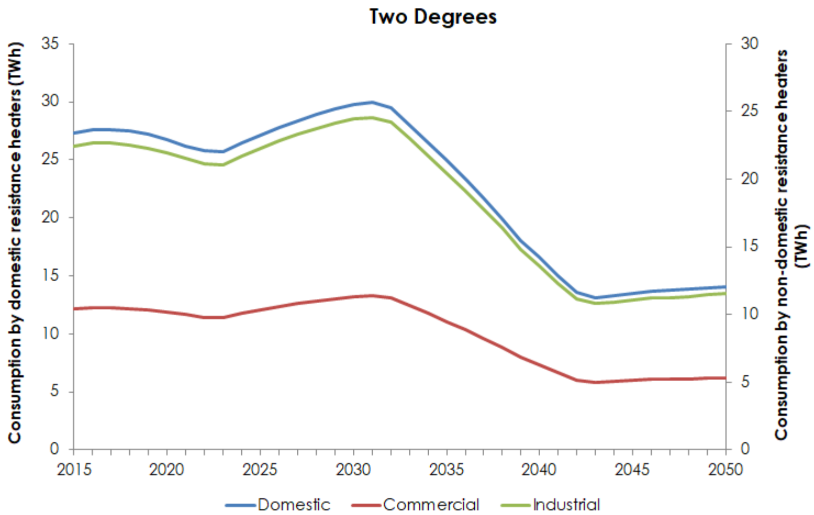


Figure 6.33: Annual consumption by resistance heaters in the Two Degrees+, 2015-2050. Source: National Grid (National Grid, 2017a)



ables or 'other_RES' (under Two Degrees+). It is possible to observe a reduction in the use of CHP (Steady State) and nuclear (Two Degrees+) and an increase in the level of consumer exports (a mix of embedded solar and power purchased from the grid) for both scenarios. This suggests that consumers reduce self-utilisation of own renewables for the purpose of serving the grid. In terms of variable renewables (wind and solar) we do not see a significant difference between the cases with and without DSM, which is explained by the fact that the algorithm does not take into

Figure 6.34: Change in GHG emissions achieved with AGG_DF relative to the base case, 2015-2050. Source: ESMA

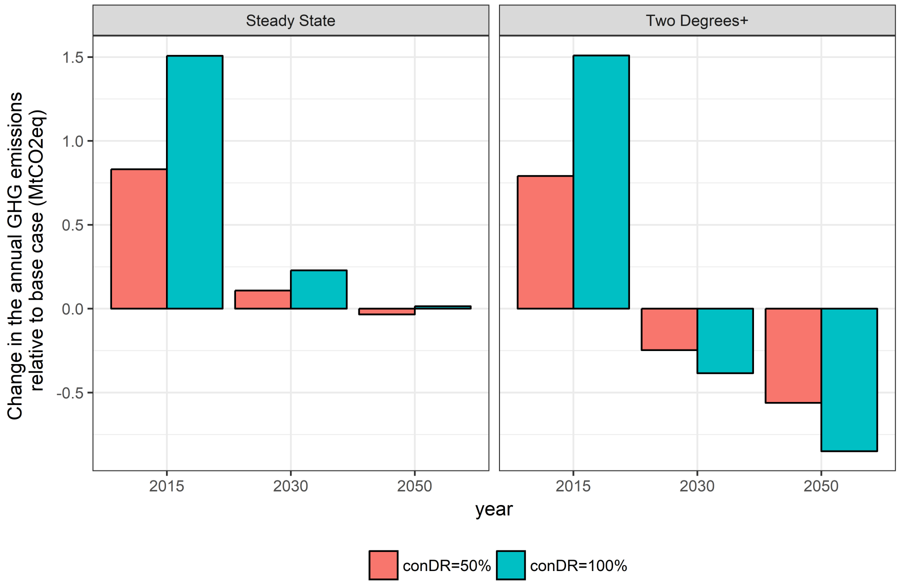
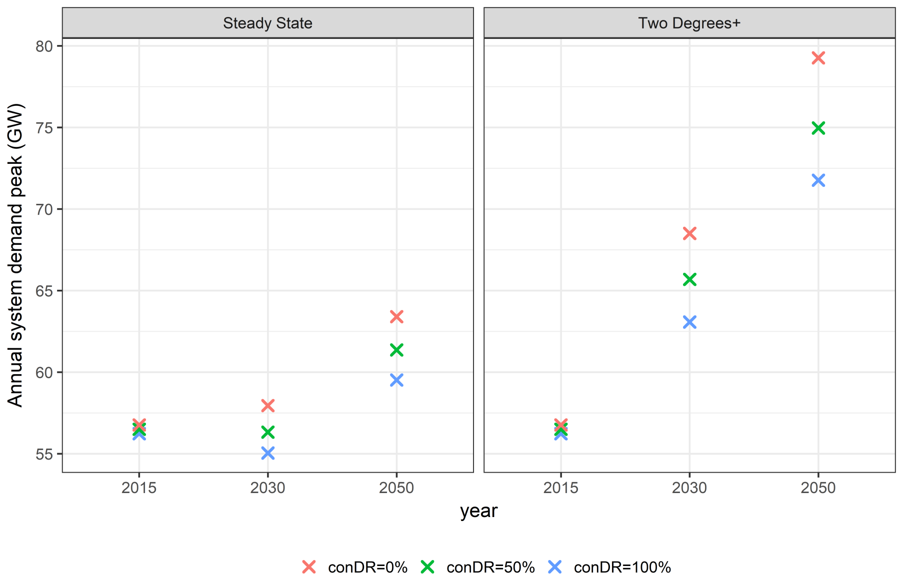
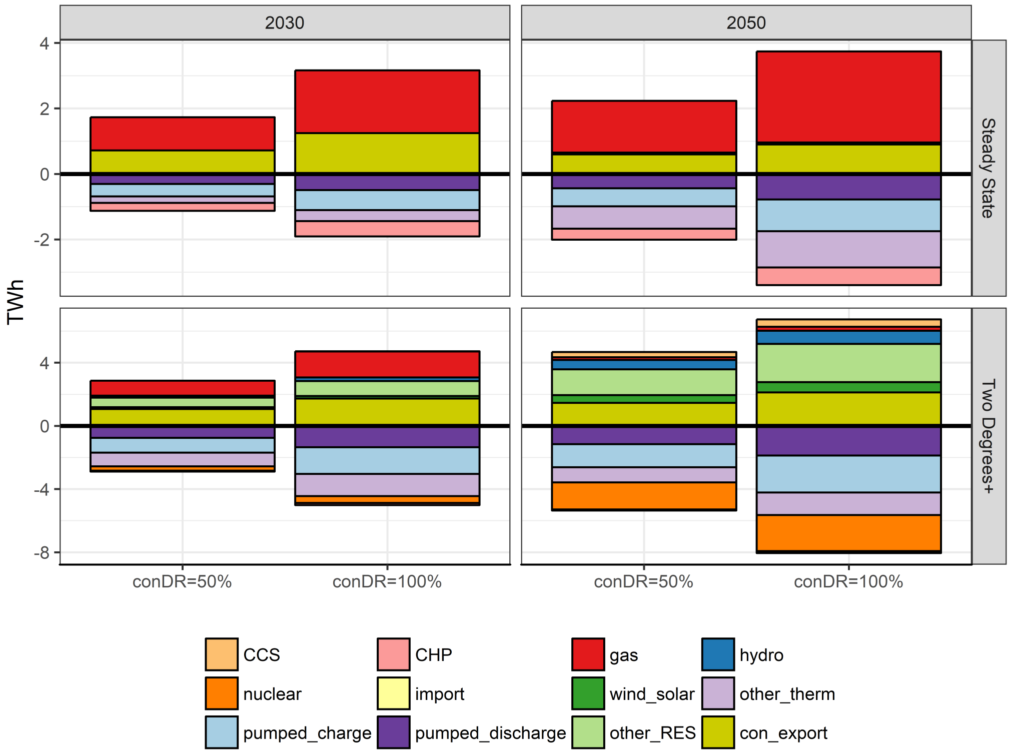


Figure 6.35: Change in the annual system demand peak with AGG_DF relative to the base case, 2015-2050. Source: ESMA



account generation from renewables at the system level. Overall the mix appears to improve, however a higher demand by the system offsets the benefits of AGG_DF and GHG savings are not as high as one might expect.

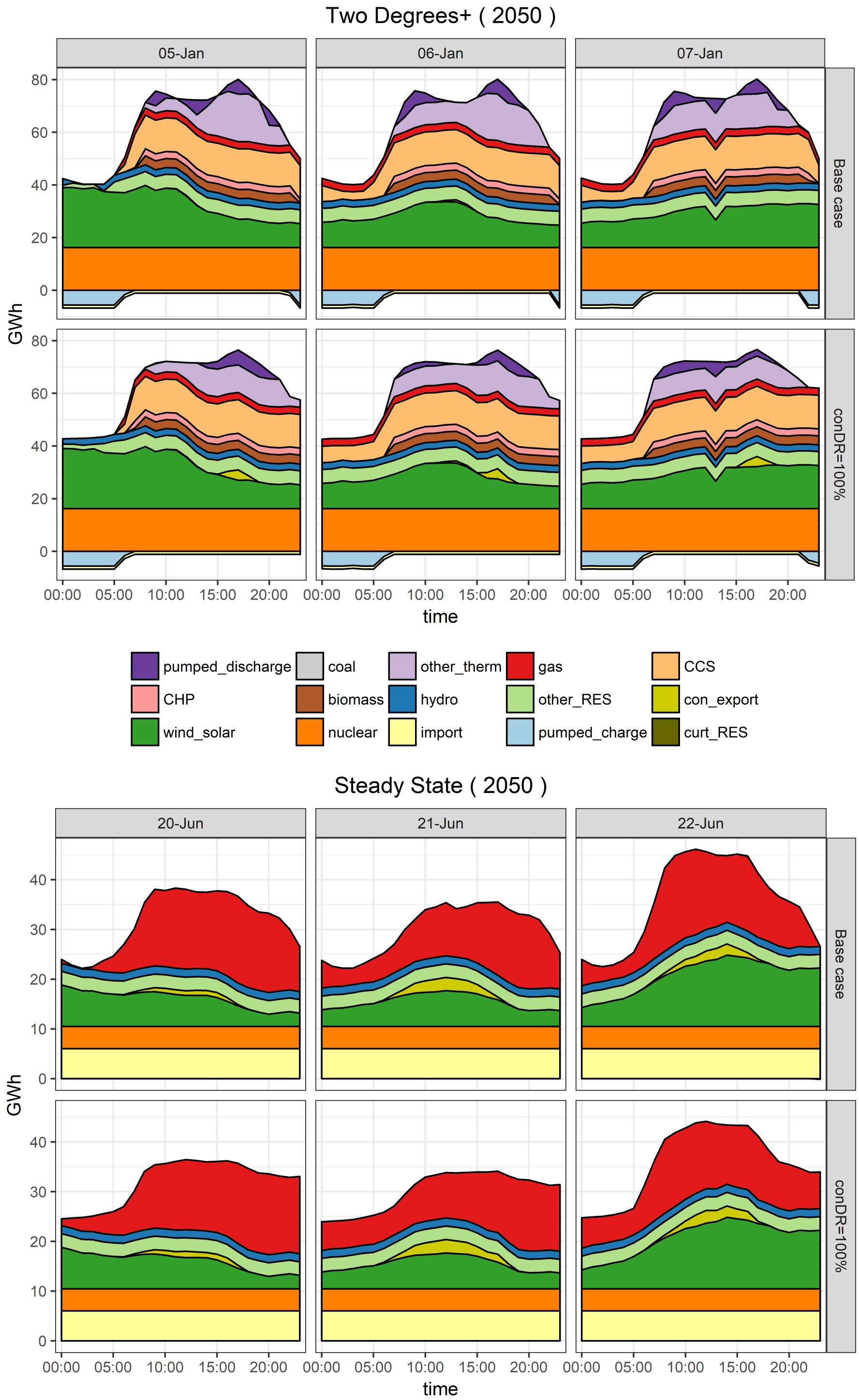
Figure 6.36: Change in the annual fuel mix under AGG_DF relative to the base case by source, 2030 and 2050. Source: ESMA.



Note: 'other_therm' includes open cycle gas turbines (OCGT), diesel and gas reciprocating engines, and fuel oil
'other_RES' includes geothermal CHP, waste CHP, anaerobic digestion CHP, landfill gas, sewage, marine and biogas CHP

Figure 6.37 demonstrates how daily generation profiles for different technologies change as a result of AGG_DF during summer and winter days in 2050 for the two boundary scenarios. It is possible to observe how a flatter demand curve leads to a smoother operation of dispatchable generators, i.e. CCS and 'other therm' (under Two Degrees+) and gas (under Steady State). The use of pumped storage also appears to marginally reduce (Two Degrees+), whereas the amount of consumer exports increases (for both scenarios). Although the difference in the generation profiles is subtle when observed for a few days, it clearly amounts to significant benefits for the system when accounted over a few years.

Figure 6.37: Daily generation with and without AGG_DF (conDR=100%) by source, winter and summer days in 2050. Source: ESMA



Note: 'other_therm' includes open cycle gas turbines (OCGT), diesel and gas reciprocating engines, and fuel oil
'other_RES' includes geothermal CHP, waste CHP, anaerobic digestion CHP, landfill gas, sewage, marine and biogas CHP

6.2.2 Consumer costs

In contrast to our observations when consumers scheduled demand autonomously (see Section 6), with AGG_DF end-users benefit from savings relative to the base case. This highlights the positive impact of a well-coordinated DSM regime. As previously described, we look at consumer bills across different consumer sectors as well as types.

6.2.2.1 Analysis of different consumer sectors

At the sector level, domestic consumers see the highest absolute savings in both Steady State and Two Degrees+ scenarios, which amount to almost £0.7 billion and £0.4 billion per year in 2050 for Two Degrees+ and Steady State scenarios respectively (Figure 6.38). This happens because domestic consumers have the highest absolute flexibility when aggregated at the sector level (due to a large number of electric heating and thermal energy storage units).

Figure 6.38: Absolute change in the annual consumer bills with AGG_DF relative to the base case by sector, 2015-2050. Source: ESMA.

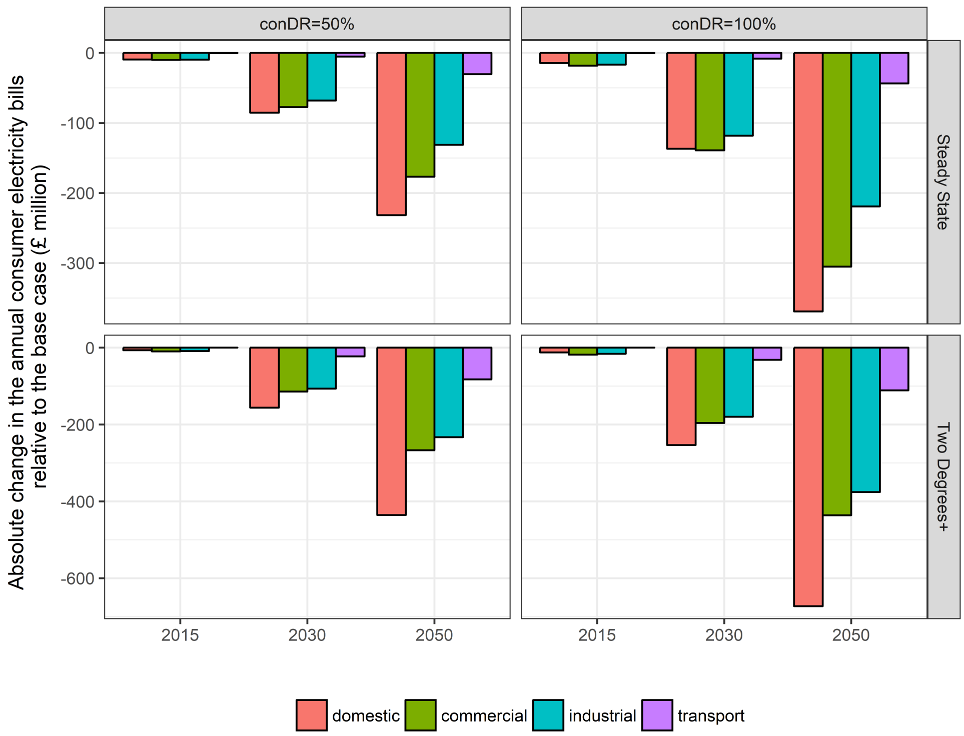
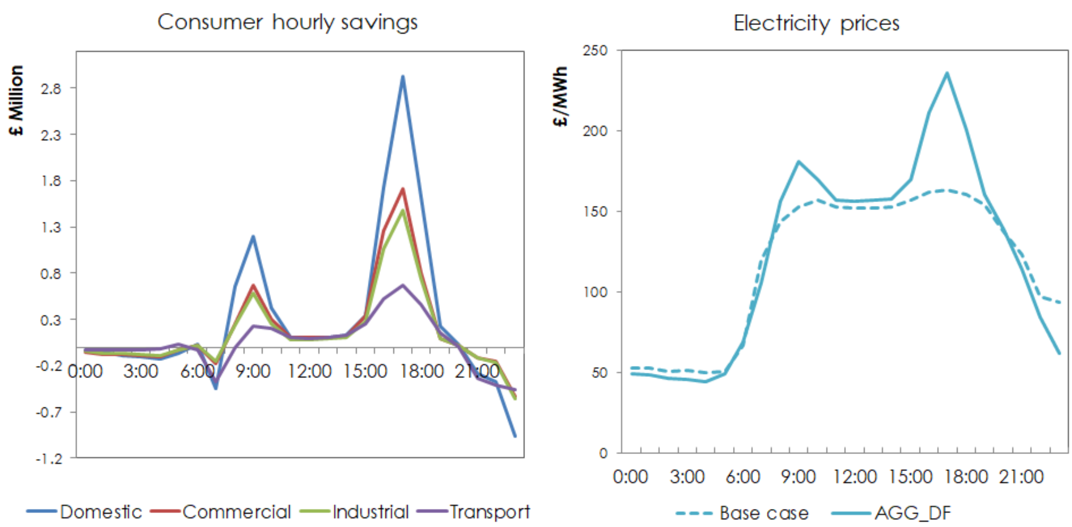


Figure 6.39 demonstrates how each sector makes savings as a result of deploy-

ing DSM for an exemplary winter day. It is possible to see that hourly savings for domestic consumers are largest during the periods of 8:00-11:00 and 15:00-17:00, which correspond to the peak hours in the base case in terms of prices (right chart in Figure 6.39). Higher flexibility of domestic consumers allows the sector to reduce demand during peak hours more compared to the other sectors leading to the highest absolute savings.

Figure 6.39: Consumer demand profiles with and without AGG_DF(conDR=100%) by sector, 24 December 2050 (Two Degrees+). Source: ESMA.



In relative terms, the domestic sector also saves the most in the Two Degrees+ case (-7%), however in the Steady State scenario it is the electric transportation which sees the highest benefits (-3.62%) (Figure 6.40). This is because in the Steady State scenario, domestic consumers experience a high demand increase due to the operation of storage. Hence relative savings (calculated as absolute savings divided by demand increase) are lower compared to the transportation sector (which experiences the same level of loses with and without DSM). To summarise, the explanation for absolute and relative savings with AGG_DF across different sectors is exactly analogous to the reasoning behind absolute and relative loses in the case of herding (see Section 6).

Figure 6.40: Relative change in annual consumer bills with AGG_DF (conDR=100%) relative to the base case by sector, 2015-2050. Source: ESMA.

Scenario	Year	Domestic	Commercial	Industrial	Transport
Base year	2015	-0.29%	-0.43%	-0.41%	-1.76%
Steady State	2030	-1.69%	-2.07%	-1.98%	-2.99%
	2050	-3.06%	-3.45%	-3.49%	-3.62%
Two Degrees+	2030	-3.68%	-3.25%	-3.14%	-2.80%
	2050	-7.02%	-5.34%	-5.20%	-5.06%

6.2.2.2 Analysis of different consumer types

Figure 6.41 demonstrates the benefits of AGG_DF for non-flexible consumers in terms of reducing the cost of an average unit of energy purchased during each year. Apart from end-users with solar PV, all non-flexible consumers benefit from a price reduction of a few £/MWh (which increases further into the future). This is especially noticeable in the Two Degrees+ scenario. Consumers with electrical heating (EH) make larger savings compared to consumers without any resources, due to a higher overall demand.

We notice that domestic consumers of type 2 (with a resistance heater, RH) see larger savings in the cost of power per unit of demand compared to those of type 1 (with a heat pump, HP), whereas for the industrial sector (and less so for the commercial) the opposite is true. This has much to do with the difference in the demand pattern for domestic and non-domestic consumers and its relation to the electricity price curve before and after coordination (Figure 6.42).

In the base case the demand profile of domestic consumers with electric heating is more correlated with prices compared to non-domestic consumers of the same type. Hence the absolute savings achieved under AGG_DF by the domestic consumers with a RH (i.e. those with a higher demand) are higher compared to those with HP (higher efficiency and lower demand). Hence, per unit savings are also higher for domestic consumers with RH relative to those with HP. Industrial consumers with EH make a saving during the off-peak times and so having a higher demand (i.e. with RH) reduces per MWh savings.

Consumers with solar PV experience an increase in the price of electricity

Figure 6.41: Change in the average electricity price for inflexible consumers with CON_CM (conDR=100%) by type, 2015-2050.

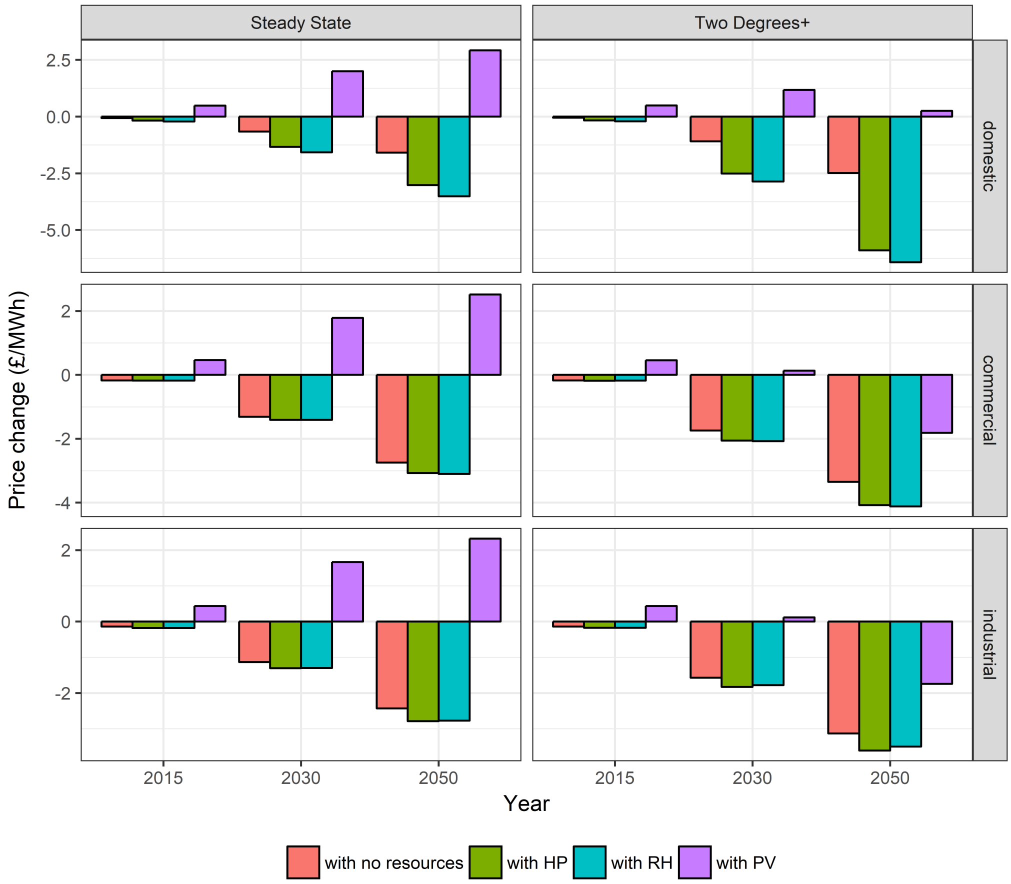
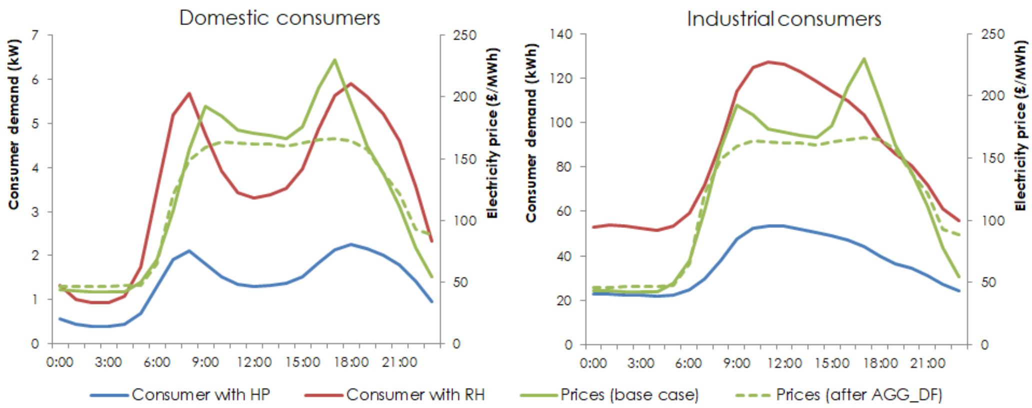
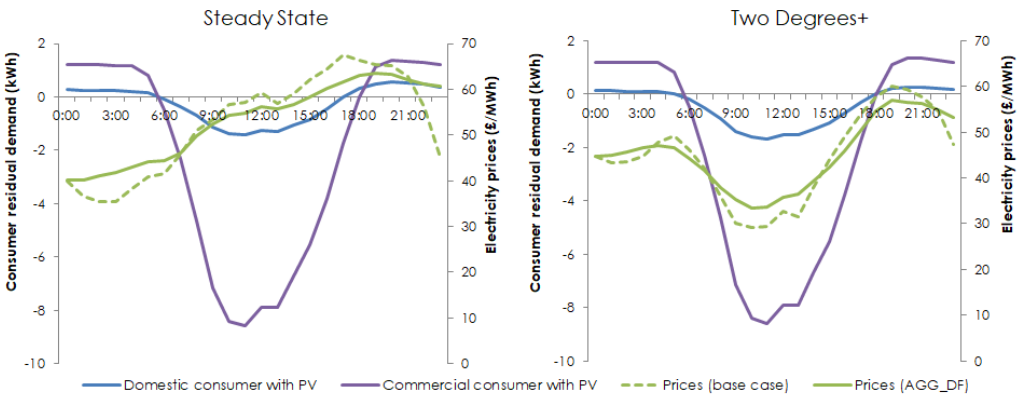


Figure 6.42: Daily demand profiles of domestic and non-domestic consumers with electric heating and electricity prices with and without AGG_DF (conDR=100%), 1 January 2050 (Two Degrees+). Source: ESMA



across all years under Steady State scenario. However in the Two Degrees+ scenario in 2050, non-domestic consumers with PV benefit from AGG_DF and see their price for electricity drop. Non-flexible domestic consumers with PV see a slight price improvement in 2050 relative to the previous years (Two Degrees+) but it is still higher than in the base case. Looking at how the residual demand profiles for domestic and non-domestic consumers stack up against electricity prices with and without DSM offers an explanation for this (Figure 6.43).

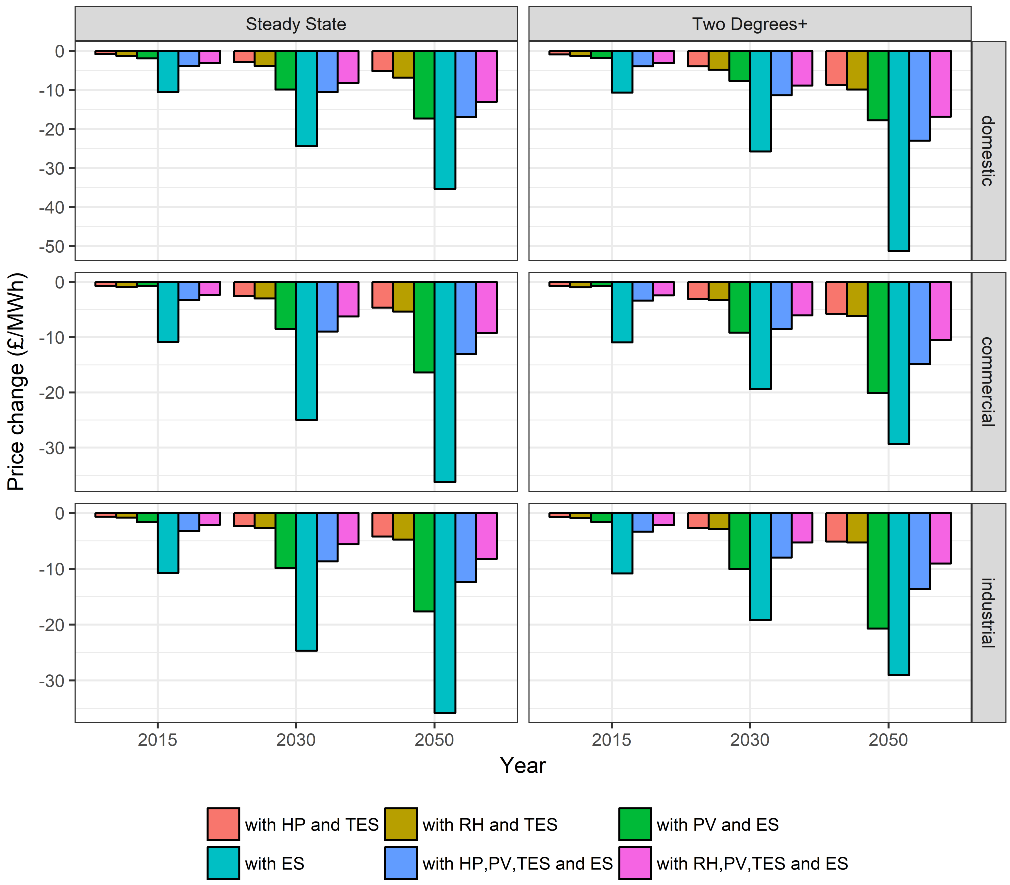
Figure 6.43: Daily demand profiles of domestic consumers with solar PV and electricity prices with and without AGG_DF (conDR=100%), 18 June 2050 (Two Degrees+). Source: ESMA.



From Figure 6.43 we can see that in the Steady State scenario the off-peak hours occur during the night (00:00-06:00) and so the effect of DSM is to raise prices during the night and decrease them during peak hours (i.e. 09:00-21:00). Hence the power from solar PV sold by consumers during the day becomes cheaper under DSM compared to the base case (assuming that sales are made at the real time price). In the Two Degrees+ scenario off-peak hours occur during the day (06:00-18:00) when generation from solar PV is abundant. The effect of DSM is to smooth demand profile and therefore raise prices during the day. Consequently, consumer exports become more profitable with DSM compared to the base case. The reason why non-domestic consumers benefit more from this situation, is because solar generation profile is more correlated with non-domestic electricity consumption. This means that non-domestic consumers self-consume more of own generation and therefore become less exposed to the import price unlike domestic consumers. In 2050 (Two Degrees+) domestic consumers see a slight reduction in the price for electricity due to the modelled energy efficiency improvements of non-deferrable demand (see D.1). As a result, their exports go up relative to the non-deferrable demand allowing consumers to make more profit from selling power in the wholesale market.

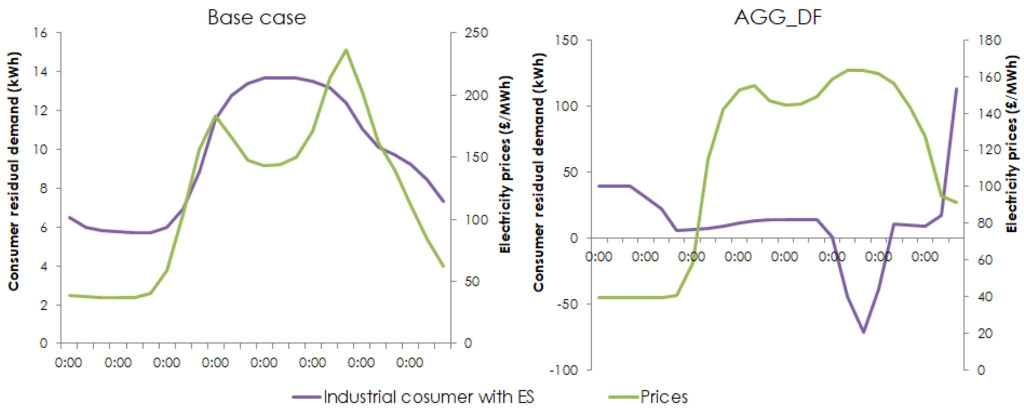
Figure 6.44 demonstrates the impact of AGG_DF on the average costs of flexible consumers. We can see that across all consumer types the impact of DSM is positive - a complete opposite to the situation observed in the case of herding.

Figure 6.44: Change in the annual electricity price for flexible consumers with AGG_DF (conDR=100%) relative to the base case by type, 2015-2050.



Consumers of type 8 (with an electrical store, ES) benefit the most from DSM and see £30-50/MWh reduction in the price for electricity per year in 2050 depending on scenario. Figure 6.45 looks at the demand profile of an industrial consumer with an ES with and without DSM. We can see that with DSM the consumer is instructed to export electricity during peak hours and increase consumption during off-peak hours in order to smooth the total system load curve and consequently prices. However, since the peak prices are not totally reduced the consumer ends up exporting during expensive time periods (17:00-21:00), which more than covers the additional purchases at night at a lower rates (00:00-03:00). According to the simulation, on the 1st of January 2050 in the Two Degrees+ scenario an industrial consumer with an ES makes a profit of around £20, which translates into 9.4 p/kWh (or 94 £/MWh) daily saving. Of course not all days during the year will lead to the same profit but averaged over the year this explains the £30/MWh reduction in the cost of power.

Figure 6.45: Daily demand profiles of industrial consumers with ES with and without AGG_DF (conDR=100%), 1 January 2050 (Two Degrees+). Source: ESMA.

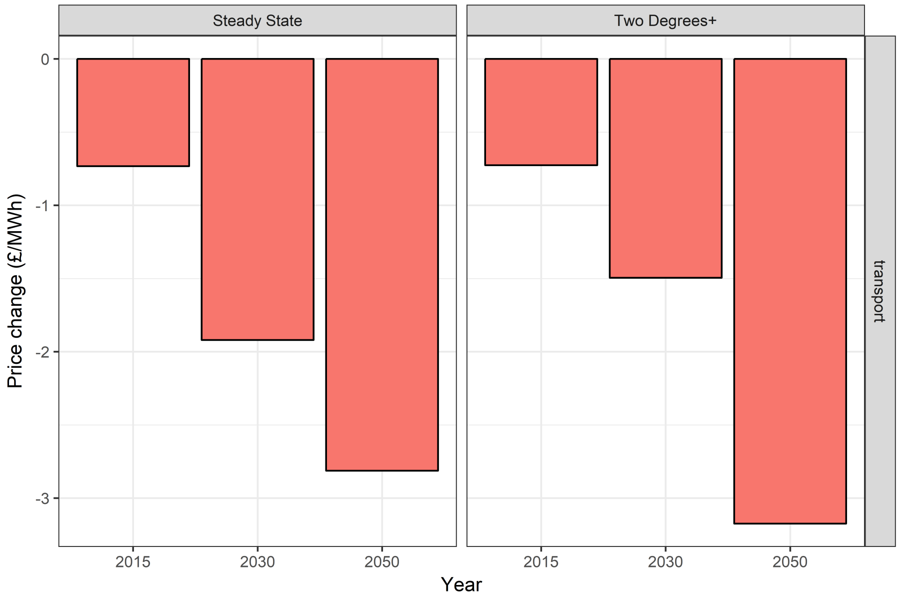


Electric transportation sees marginal benefits from DSM since vehicle-to-grid discharging is not allowed in the model (Figure 6.46). This substantially reduces the flexibility of EVs compared to some larger consumers with electrical stores like industrial end-users. Overall, we observe that higher ratio of consumer storage capacity to demand lead to a larger reduction in the price. Consumers with PV are an exception since, their profits from exports are affected during coordination as described earlier.

6.2.3 When aggregators get greedy

In the previous section we observed the benefits of a well-coordinated DSM, whereby an aggregator schedules consumer demand for the purpose of smoothing system demand peaks. However, it is easy to imagine that aggregators (especially those representing utilities) will exploit the ability to shift consumer demand for

Figure 6.46: Change in the annual electricity price for electric vehicles with AGG_DF (conDR=100%) relative to the base case, 2015-2050. Source: ESMA.

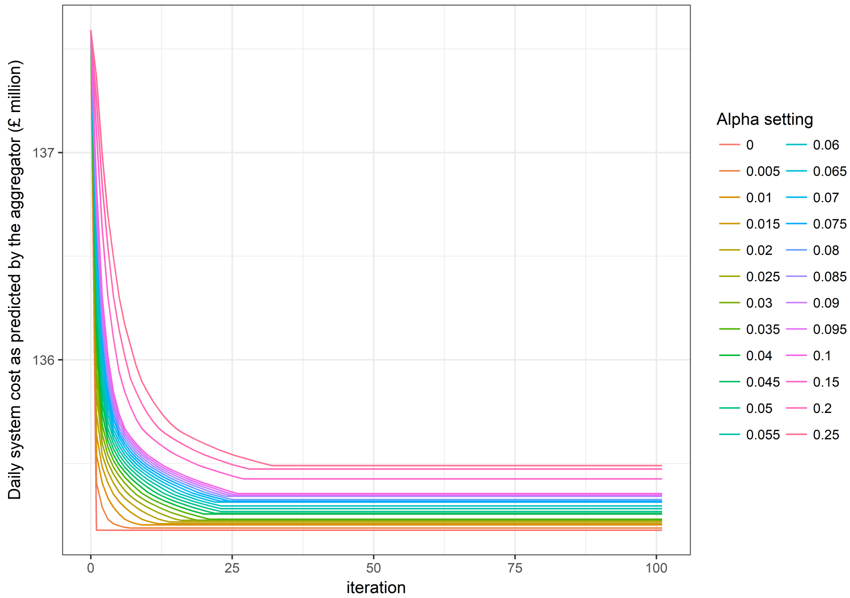


the purpose of increasing profit by minimising the cost of power purchased from the market. This effect is simulated by deploying algorithm AGG_CM, whereby the aggregators communicate to consumers the predicted real time prices for electricity rather than the average demand (see section 3.5). The aggressiveness of the aggregators to cost minimise is controlled through parameter α, which penalises consumers for shifting from the previous demand profile during the aggregator-consumer negotiation process (see Section 3.5). To remind the reader, when α is large consumers do not deviate much from their default demand, whereas when α is small they are free to cost minimise as much as they want. In this sense, α acts as a control parameter for how much flexibility end-users are allowed to use.

Figure 6.47 demonstrates how the projected cost of aggregator power is reduced during the coordination process with different α settings. It can be seen that with a lower α, the aggregator is more efficient in reducing the projected cost. When $\alpha = 0$ consumers converge after only one iteration, which is not surprising since this corresponds to the case when consumers are not penalised for shifting demand at all and so they maximise the utilisation of storage.

Figure 6.48 shows how system savings from DSM are affected when aggre-

Figure 6.47: Demonstration of the reduction in the projected cost of power purchased by the aggregator with varying α settings for AGG_CM (conDR=100%, aggDR=100%), 1 Jan 2050 (Two Degrees+). Source: ESMA.



gators reduce the α parameter. We can see that higher α settings lead to positive system savings (meaning a reduction in the total system cost), whereas lower α values lead to negative savings (i.e. an increase in the system cost). Hence when aggregators become more aggressive in minimising cost, they end up herding towards the same periods of low electricity prices - similarly to the scenario when consumers cost minimise autonomously with CON_CM.

It is suspected that when the share of cost minimising aggregators is low, those that do, will see an advantage over those which are passive. In order to demonstrate this, four aggregators are modelled (each with an equal pool of consumers) and only one of them is allowed to cost minimise. This scenario mimics the situation when a quarter of the aggregator market adopt AGG_CM for the purpose of cost minimisation.

When observing the annual tariffs offered by aggregators, we can see that the aggregator which cost minimises has an advantage over those which do not (Figure 6.49). Consumers are likely to pick an aggregator which offers a lower electricity tariff and so it makes sense for the aggregators to adopt this strategy, which can lead to the market herding (as demonstrated Figure 6.48).

Figure 6.48: Annual system cost as aggregators adopt AGG_CM (conDR=100%, aggDR=100%), 2015-2050. Source: ESMA.

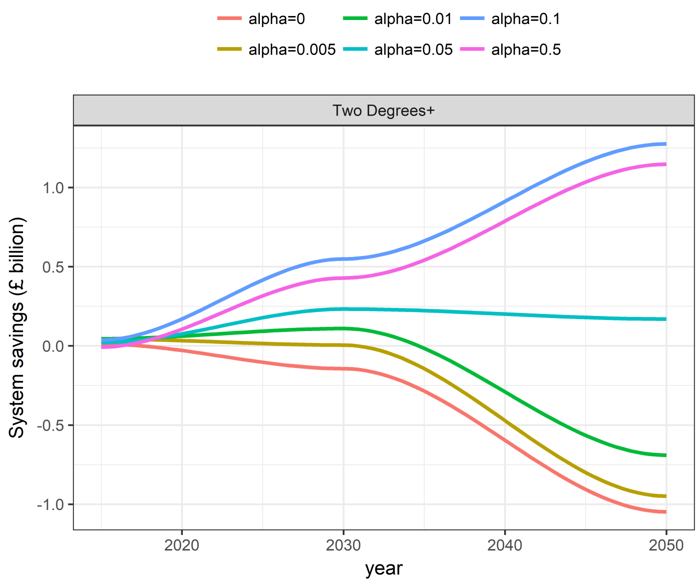
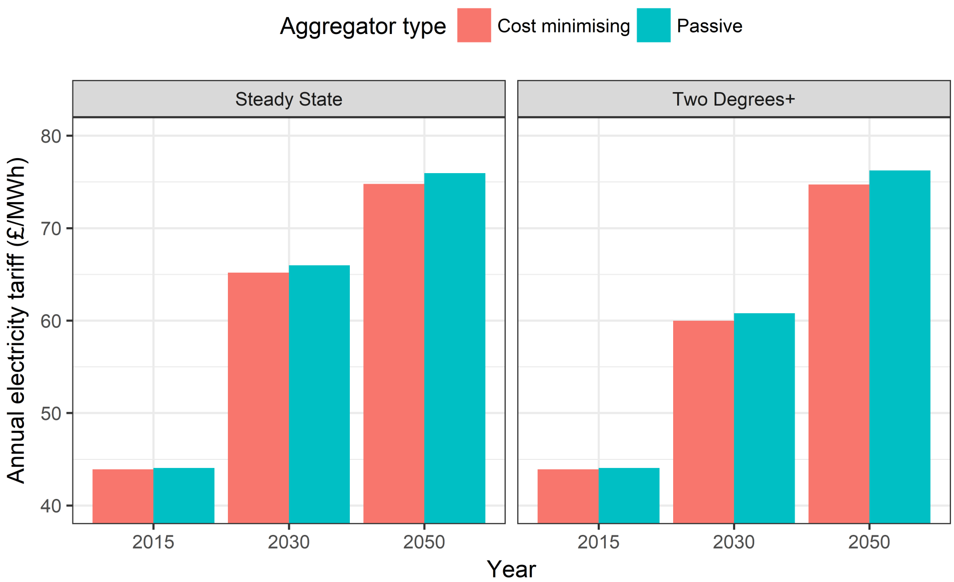


Figure 6.49: Comparison of electricity tariffs between a cost minimising aggregator and a passive aggregator (aggDR=25%), 2015-2050. Source: ESMA.



6.2.4 The impact of retail market competition under DSM on the system

Consumers are notoriously passive when it comes to switching their energy providers. However, a recent report by The Office of Gas and Electricity Markets

(Ofgem) shows that in the UK electricity switching rate has gone up by 30% in 2017 relative to 2015 and reached a 6-year high (4.4 million consumers)(Ofgem, 2017c). This spike has been largely driven by the emergence of new smaller and medium size suppliers offering more flexible and transparent tariffs (e.g. (Energy, 2018)), as well as companies providing switching services on behalf of the consumer, e.g (Switchcraft, 2018). With the integration of smart metering services and increased consumer awareness of climate change issues, it is expected that end-users will become more engaged in choosing the right energy provider for them. As discussed in the previous section, it is highly likely that aggregators will utilise DSM to win over consumers. Hence, it is of relevance to investigate how consumer switching rates will impact the electricity system.

In order to do that, we model two cost minimising aggregators competing for consumers in 2050 (Two Degrees+) based on the average daily price of electricity. Here we model an uneven number of consumers per aggregator to start off with in order to introduce some competition (Figure 6.50).

Figure 6.50: List and number of consumers signed up with each aggregator on day one of the simulation, 2050 (Two Degrees+). Source: ESMA.

Aggregator 1	Aggregator2
• 10,281,729 - domestic (no resources)	• 11,074,781 - domestic (with HP)
• 1,410,594 - domestic (with HP and TES)	• 650,347 - domestic (with RH)
• 303,845 - domestic (with RH and TES)	• 1,930,275 - domestic (with PV)
• 173,722 - domestic (with PV and ES)	• 6,092 - domestic (with ES)
• 185,614 - domestic (with HP, PV, TES and ES)	• 60,706 - domestic (with RH, PV, TES and ES)
• 4,238,516 - commercial (no resources)	• 550,096 - commercial (with HP)
• 105,545 - commercial (with HP and TES)	• 55,575 - commercial (with RH)
• 100 - commercial (with RH and TES)	• 250,732 - commercial (with PV)
• 100 - commercial (with PV and ES)	• 90,875 - commercial (with ES)
• 100 - commercial (with HP, PV, TES and ES)	• 100 - commercial (with RH, PV, TES and ES)
• 677,693 - industrial (no resources)	• 86,807 - industrial (with HP)
• 34,240 - industrial (with HP and TES)	• 21,249 - industrial (with RH)
• 100 - industrial (with RH and TES)	• 57,238 - industrial (with PV)
• 100 - industrial (with PV and ES)	• 18,564 - industrial (with ES)
• 100 - industrial (with HP, PV, TES and ES)	• 100 - industrial (with RH, PV, TES and ES)
• 16,567,605 - transport	

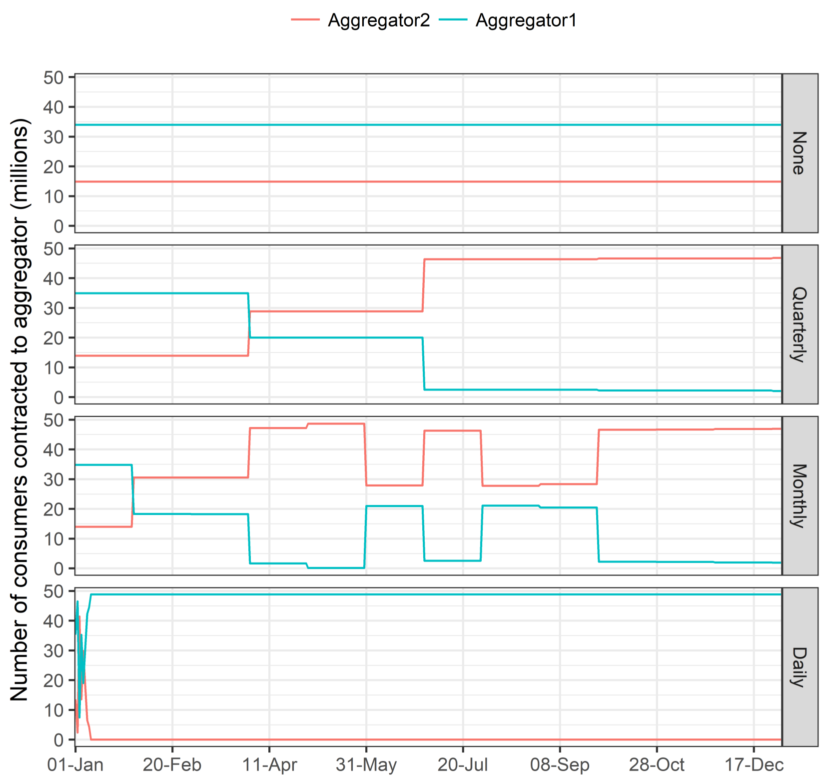
Aggregator 1 is contracted to all consumers of type 1 (no resources), type 3 (with HP and TES), type 5 (with RH and TES), type 7 (with PV and ES), type 9 (with HP, PV, TES and ES), and the whole fleet of electric vehicles. Aggregator 2 is contracted to consumers of type 2 (with HP), type 4 (with RH), type 6 (with PV), type 8 (with ES), and type 10 (with RH, PV, TES and ES). As a result Aggregator 1 has access to more storage and Aggregator 2 has more solar capacity (hence a lower demand). Consumers are then allowed to switch aggregators according to four cases: no switching, quarterly, monthly and daily. 50% of consumers are allowed to switch when the time comes - a value set arbitrarily for demonstration purposes. The stylised nature of this experiment is acknowledged, however considering the difficulty in obtaining consumer information regarding their energy service providers, it is deemed to be sufficient to demonstrate the potential issues that may arise as a result of retail market competition in the context of DSM.

Figure 6.51 shows how consumers migrate between the two aggregators during the experiment. The aggregators calculate the retail electricity tariff as a running average of the break-even cost of purchasing electricity. Hence, monthly switching corresponds to long-term decision making by consumers, whereas daily switching corresponds to short-term decision-making.

With quarterly switching, aggregator 1 slowly loses consumers whilst aggregator 2 gains them even though it starts with fewer. When consumers switch on a monthly basis, aggregator 1 alternates between losing and gaining the market share. However, when consumers switch daily, aggregator 1 wins the whole consumer market in the first few days of the year. The competition dynamic between the two aggregators comes as a result of each one having different flexibility resources and demand constraints. Hence, a daily win can be critical to gaining the higher share of the consumer market.

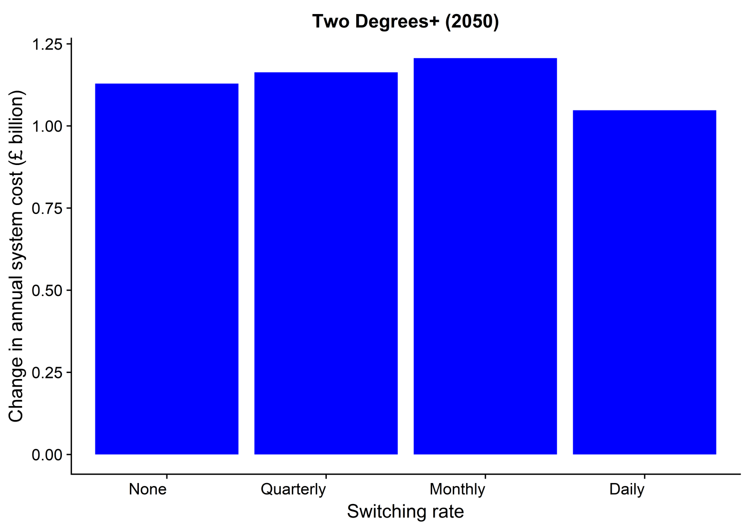
Such competition can carry negative consequences for the system. Figure 6.52 reports on the system cost increase relative to the base case (when all agents are passive) for different experimental settings. All cases when aggregators cost minimise lead to an increase in the system cost. Interestingly, the case when consumers switch daily leads to a slightly better outcome compared to the other cases. This not surprising since during daily switching all consumers end up with one aggregator

Figure 6.51: Demonstration of how consumer migrate between aggregators when they are allowed to switch at different rates, 2050 (Two Degrees+).



Key: 'None' - consumers do not switch, 'Daily' - consumers switch every day, 'Monthly' - consumers switch every 30 days, 'Quarterly' - consumers switch every 90 days

Figure 6.52: Annual system cost under different consumer switching strategies, 2050 (Two Degrees+). Source: ESMA.



rendering a more centralised DSM. The highest cost is reached when consumers switch on a monthly basis, which is also the case where both aggregators remain in the game. In fact, with monthly switching one aggregator ends up with the largest share of consumers with solar PV, allowing it to export energy into the grid and profit from the market. As a result of aggregator exports, the demand curve at the system level become more volatile and prices increase as a result. The aggregator without solar ends up demanding more from the wholesale market further contributing to the wholesale prices increase.

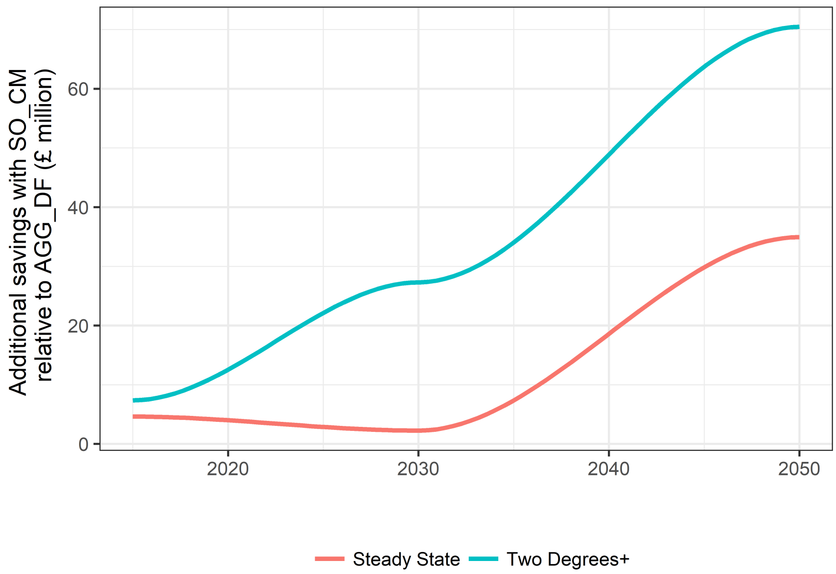
A note on vertically integrated utilities. In the above experiment it was possible to demonstrate that competition between aggregators by means of shifting demand can lead to increased system costs. In (Subkhankulova et al., 2017b,c,a) we extend this discussion to examine how vertically integrated utilities can benefit from strategically manipulating consumer loads. We compare two types of utilities performing DSM: a green one (in possession of a wind generator) and a traditional one (in possession of a dispatchable generator). We find that conditions exist where the traditional utility benefits from instructing consumers to increase demand, which allows it to sell power at a higher rate. This ultimately leads to higher system demand peaks, costs and prices for consumers. As a result of such competition, the traditional utility is able to offer a more competitive tariff for electricity compared to the green utility even though the tariffs in general are higher. Another paper which investigates this issue is proposed by (Prüggler et al., 2011), where the authors explore the consequences of vertically integrated utilities strategically operating storage. They find that in the long run electricity prices increase which suggests potential risks of vertically integrated utilities shifting demand for the purpose of competition.

6.2.5 The value of a central coordinator

One way to avoid aggregator herding is to involve a central entity like the System Operator in the coordination process. Assuming the SO is able to communicate with the market, the price information passed onto the aggregators (and further to consumers) will reflect the true cost of generating electricity and stop them from overshooting when scheduling demand. To demonstrate the benefits of a centrally-led DSM algorithm SO_CM is deployed, which is developed from AGG_DF by introducing another layer of coordination between the SO and the aggregators (see section 3.5.3).

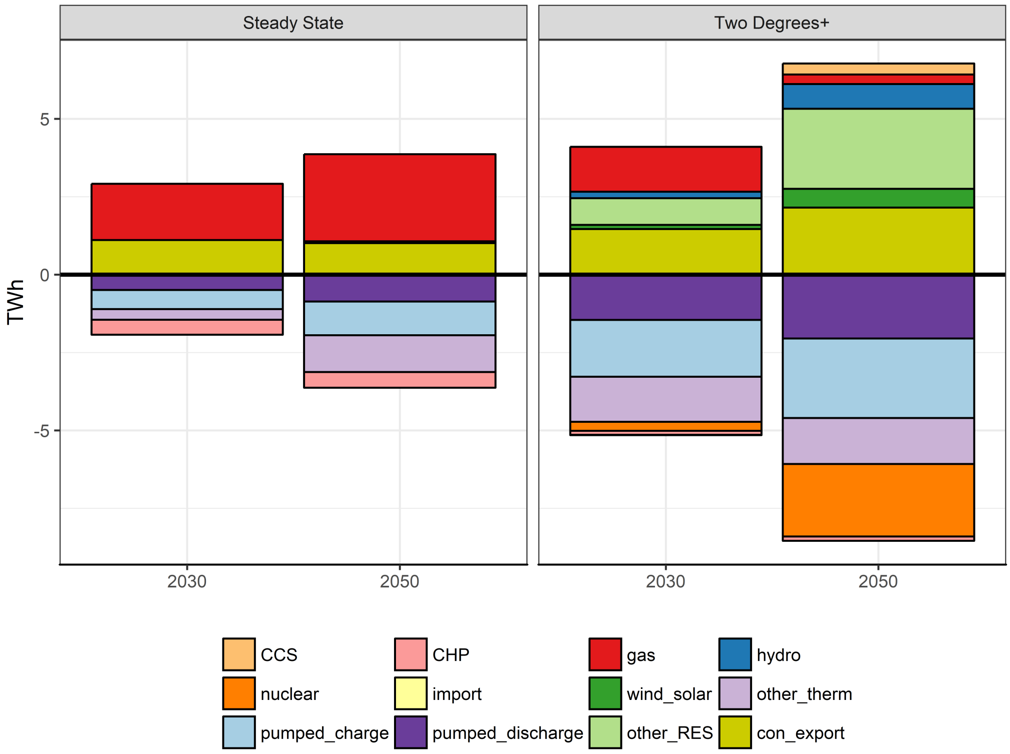
Figure 6.53 shows additional savings achieved as a result of introducing a central coordinator. We note that the system saves more in the Two Degrees+ scenario which is due to a higher consumer flexibility assumed for this scenario. Looking at Figure 6.54, we observe that the algorithm makes better use of system level renewables, which leads to a reduction in the cost of generating power and the level of GHGs emitted by the electricity grid (Figure 6.55).

Figure 6.53: Additional annual system savings with SO_CM compared to AGG_DF, 2015-2050. Source: ESMA.



Similarly to AGG_DF, with SO_CM the system utilises less pumped storage and polluting thermal generators (e.g. diesel, fuel oil and OCGT). The increase in the demand from operating storage is met by gas as well as increased consumer exports. Although regime SO_CM shows superiority over AGG_DF, appears to be marginal highlighting the limitations of ESMA. The generation component in ESMA functions on the day-ahead basis and so does not demonstrate the value of short-term coordination between demand and supply which is deployed during the

Figure 6.54: Change in the annual fuel mix with SO_CM relative to the base case, 2015-2050. Source: ESMA.



Note: 'other_therm' includes open cycle gas turbines (OCGT), diesel and gas reciprocating engines, and fuel oil
'other_RES' includes geothermal CHP, waste CHP, anaerobic digestion CHP, landfill gas, sewage, marine and biogas CHP

balancing market. For this reason the savings reported in this work are lower when compared to other papers, e.g. (Strbac et al., 2012) where the authors report £0.8-14.9 billion/year savings from balancing technologies in 2050 depending on the scenario.

Figure 6.55: Avoided GHG emissions with SO_CM compared to AGG_DF, 2015-2050. Source: ESMA.

6.2.6 Dynamic versus flat tariffs

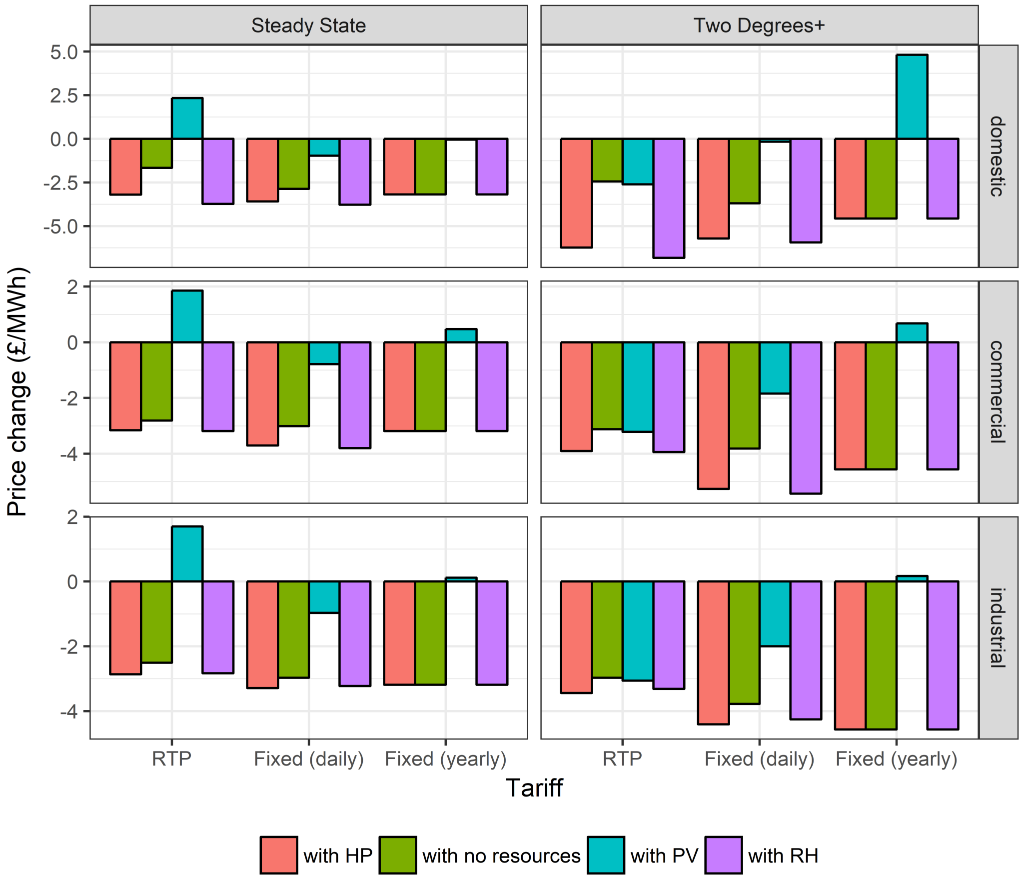
So far we have only considered billing consumers at the real time price. It has been observed that consumer demand pattern plays an important role in determining the benefits from DSM. However, since the aggregators instruct end-users on how to shift demand it might seem unfair to expose end-users to the wholesale market price risk. In this section we explore how consumer benefits are impacted when they are charged at fixed tariffs rather than dynamic electricity prices.

Figure 6.56 reports savings made by non-flexible consumers as a result of deploying DSM calculated at different retail tariffs: fixed (daily), fixed (yearly) and RTP (see Section 3.4.3.3 for calculations)[4]. We focus on 2050 (Two Degrees+) since that is the year which saw the biggest impact of DSM on consumer bills.

It is possible to see that consumers with PV are the most vulnerable to the tariff structure, especially in the domestic sector. If in the Steady State scenario they benefit more from a fixed tariff (daily rather than yearly), in the Two Degrees+ RTP leads to higher savings. This is because consumers with PV export electricity during the day, hence their cost of power is dependent on the price at which they

[4]We take regime AGG_DF as an example since the results are very similar to SO_CM

Figure 6.56: Comparison of non-flexible consumer savings with AGG_DF accounted at different tariffs, 2050. Source: ESMA.

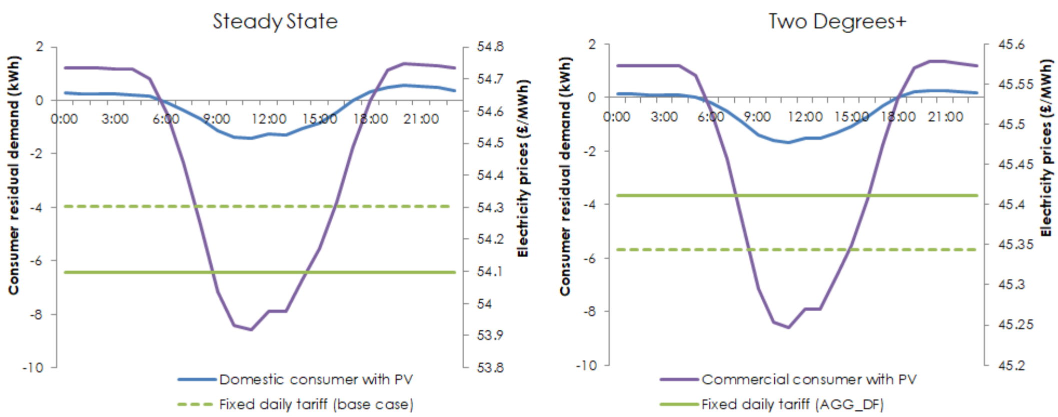


sell electricity. Domestic consumers with PV are more vulnerable to the electricity tariff structure compared to non-domestic consumers of the same type, since their demand profile is less correlated with the generation profile from solar and so they rely on exporting electricity at the peak prices (such as in the case of RTP in the Two Degrees+ case).

Figures 6.57 and 6.58 demonstrate how electricity tariffs change against residual demand profiles for domestic and non-domestic consumers with PV. The analysis focuses on a summer day since it corresponds to the situation where the generation from solar PV is abundant.

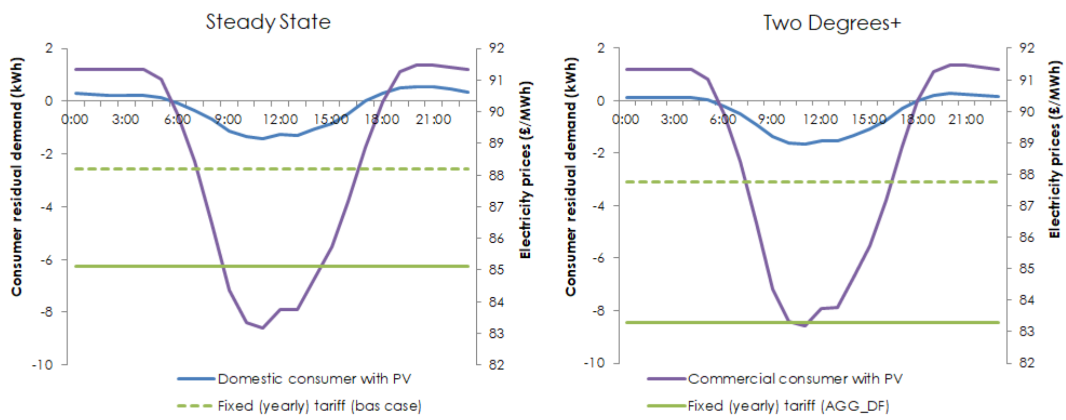
In the case when tariffs are calculated at an average daily rate, DSM leads to a reduction in the tariffs in the Steady State and an increase in the Two Degrees+ scenario (similarly to RTP) (Figure 6.57). Hence in the Two Degrees+ scenario, power exported by consumers with DSM will be more profitable with DSM relative to the base case. However, since a flat tariff ignores the correlation between wholesale prices for electricity and the solar generation profile (i.e. only the amount of energy exported matters), in the Two Degrees+ scenario consumers benefit less when exporting at a flat daily rate rather than RTP. In the Steady State scenario consumers see a drop in electricity prices due to the overall cost of purchased energy going down. Domestic consumers with PV see almost no benefit from DSM in the Two Degrees+ scenario when billed at the fixed daily rate. This is because residential consumers purchase more power compared to what they export and rely on the correlation between the generation and price profile (as demonstrated in Figure 6.57).

Figure 6.57: Daily demand profiles of domestic and commercial consumers with PV against fixed daily electricity tariffs with and without AGG_DF (aggDR=100%, conDR=100%), 2050. Source: ESMA



When consumer tariffs are calculated on an annual basis, we note that for both Steady State and Two Degrees+ scenarios the average price level drops under DSM (Figure 6.58). Hence, consumers with PV benefit less from exports and see an increase in the cost of power. However, in the Steady State all consumers still perform better with fixed pricing relative to RTP. In the Two Degrees+ scenario domestic consumers with PV are most exposed when billed at the fixed annual tariffs and see the price of electricity increase by £5/MWh. This is because in the Two Degrees+ scenario average annual tariffs experience a large drop under DSM.

Figure 6.58: Daily demand profiles of domestic and commercial consumers with PV against fixed yearly electricity tariffs with and without AGG_DF (aggDR=100%, conDR=100%), 2050. Source: ESMA

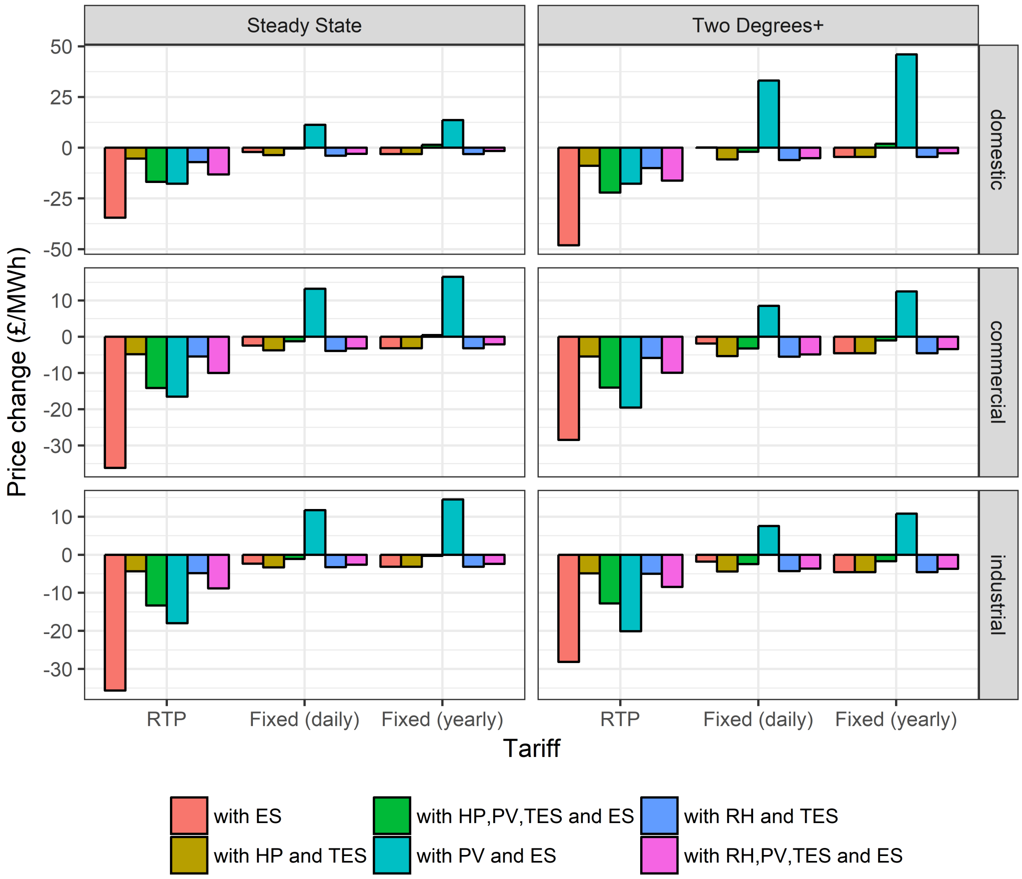


Non-domestic consumers with electric heating appear to benefit more from DSM when billed at the fixed daily price, which suggests that their demand profiles are less correlated with the price curve in the base case. For the same reason in the Two Degrees+ scenario, industrial end-users with no resources benefit the most when billed at the fixed annual rate.

Across all scenarios, flexible consumers save more when billed at the real time price, with consumers of types 7 (with PV and ES) and 8 (with ES) benefitting the most (Figure 6.59). It appears that consumers with more flexibility and less demand are impacted more compared to the more inflexible and less consuming end-users. For this reason consumers with PV and ES see an increase in the price level for fixed tariff cases relative to the base case.

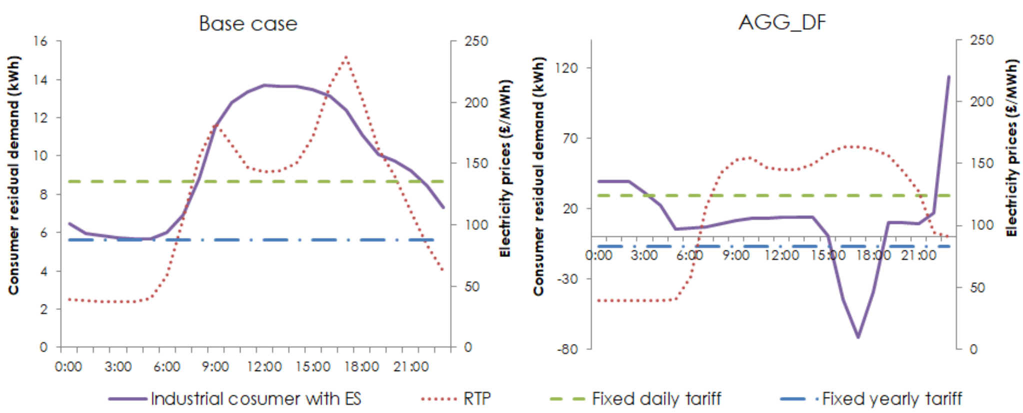
Figure 6.60 analyses the demand profile of an industrial consumer with electrical storage against fixed and dynamic electricity tariffs. As discussed before, flexible consumers are instructed to decrease demand during peak hours for which reason those with the highest flexibility end up exporting electricity. However, since the wholesale price curve (at RTP) is not totally smooth they export electricity at the peak price whilst buying at a lower rate (overnight). When the prices are flat during the day consumers buy and sell at the same rate and so the profits are smaller, whilst the cost of purchased electricity is higher leading to lower overall savings.

Figure 6.59: Comparison of flexible consumer savings with AGG_DF (aggDR=100%, conDR=100%) accounted at different tariffs, 2050. Source: ESMA



Consumer profits are lowest with fixed annual prices since the overall price shift is smaller during the year reducing the arbitrage opportunity.

Figure 6.60: Daily demand profile of an industrial consumer with an electrical store (ES) against fixed electricity tariffs and RTP with and without AGG_DF (aggDR=100%, conDR=100%). Source: ESMA



Interestingly, electric vehicles benefit from a fixed tariff even though they also represent consumers with an electrical store. On a closer look (Figure 6.62) we see that under coordination the demand profile of an electric vehicle fleet goes from an almost flat one to a very variable one. Hence, in the case of RTP the demand peaks of electric transportation end up coinciding with the wholesale price peaks. When the tariffs are flat electric vehicles are protected from the wholesale market risk.

Figure 6.61: Comparison of electric transportation savings with AGG_DF (aggDR=100%, conDR=100%) relative to the base case accounted at different tariffs, 2050. Source: ESMA.

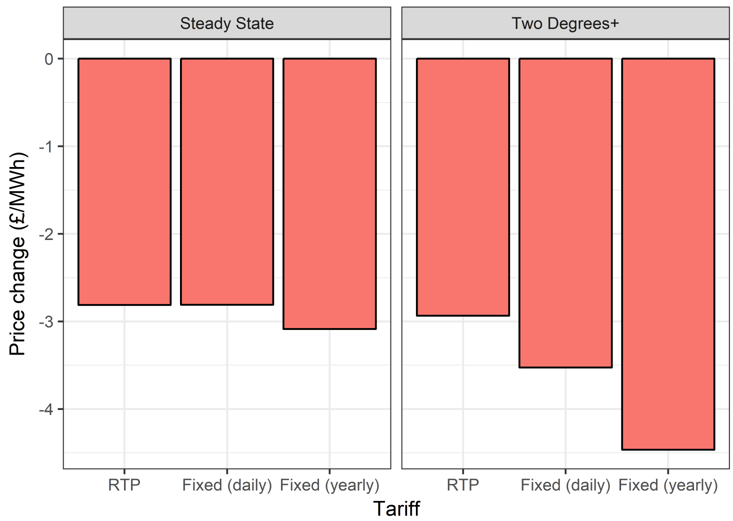
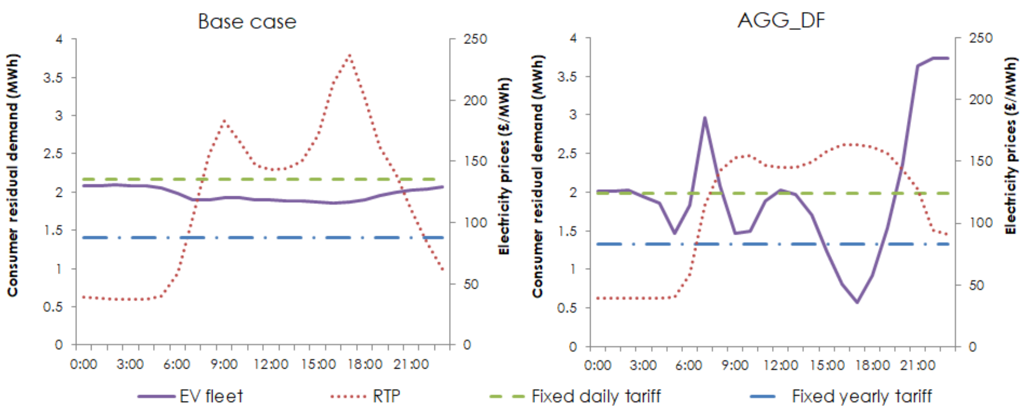


Figure 6.62: Daily demand profile of an electric vehicle fleet against fixed electricity tariffs and RTP with and without AGG_DF (aggDR=100%, conDR=100%). Source: ESMA.



6.2.7 Sensitivity analysis

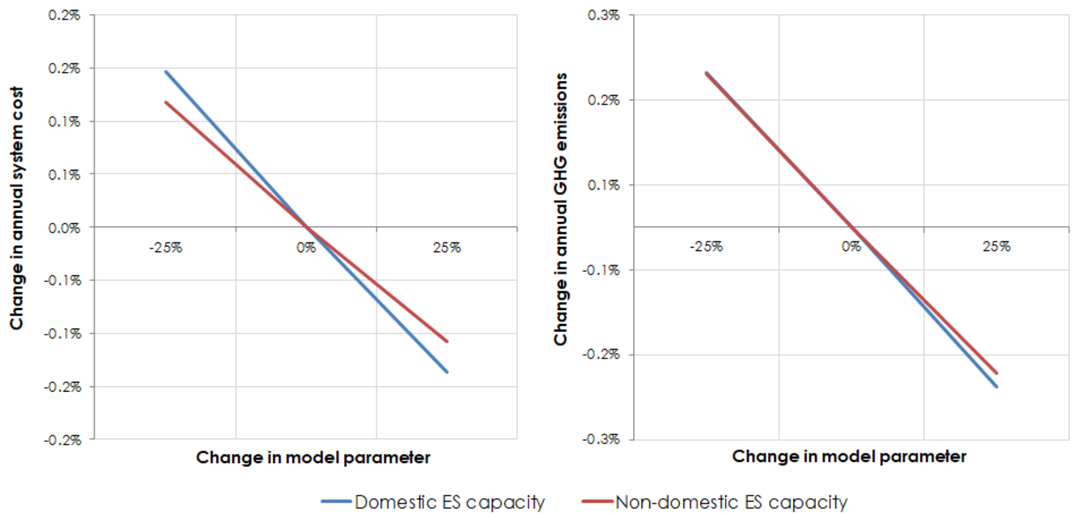
As we have seen in the analysis, electrical storage (ES) capacity plays a critical part in the level of benefits gained by consumers from the deployment of DSM. The impact on the results is explored by varying the amount of electrical storage assumed for different consumer sectors. The analysis is performed for 2050 in the Two Degrees+ scenario when all consumers participate in DSM (conDR=100%) since it constitutes the case when the system has the highest capacity of renewables and consumer storage.

Figure 6.63 demonstrates how annual system cost and the level of GHG emissions change with different values for consumer ES capacity. Not surprisingly system cost decreases whilst emissions go down when storage capacities across different sectors increase. This is because with more storage the system has more flexibility to perform demand smoothing, which leads to better utilisation of renewables and lower electricity prices. We note that system cost is more sensitive to domestic rather than non-domestic storage[5]. This is because the number of heat pumps (and consequently thermal energy stores) is assumed to be higher in the domestic sector compared to non-domestic sectors. Therefore, increasing ES capacity allows domestic consumers to shift thermal demand, whereas non-domestic consumers have less capacity to do this.

From Figure 6.64 we see that increasing consumer storage has a positive impact on consumer savings, which is in-line with our earlier observations of system costs. We note that the level of savings for each stationary sector is most sensitive to its own ES capacity followed by domestic. This is not surprising since it decreases consumer exposure to the market prices. The transport sector experiences very marginal sensitivity to the ES storage capacity across the stationary sectors seeing the level of savings change by $< 1\%$ for a 25% change in the storage capacity across the stationary sectors. Moreover, the sector appears to benefit from a reduction in the domestic storage capacity. This is because the electric transportation constitutes the most flexible consumer, and so under AGG_DF its profile is almost flat. There-

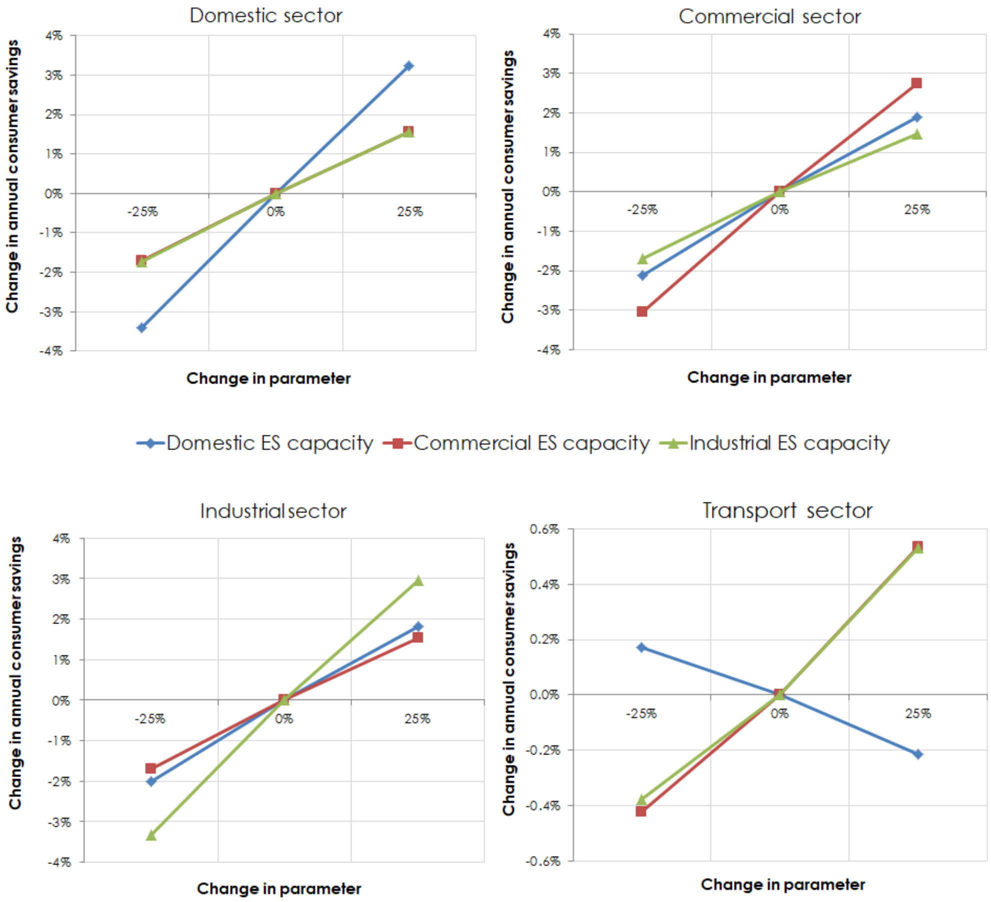
[5]Commercial and industrial sectors have been grouped as the sensitivities were very similar

Figure 6.63: Sensitivity of system cost and GHG emissions to consumer electrical storage (ES) capacity with AGG_DF (aggDR=100%, conDR=100%), 2050 (Two Degrees+). Source: ESMA.



fore, slight fluctuation in the wholesale prices have a very marginal effect on the level of savings made by the transport sector. Since during AGG_DF, consumers are negotiated with as a pool, it appears that higher storage capacity assumed in the domestic sector changes the transport demand profile in a way that leads to slightly lower savings relative to the base case.

Figure 6.64: Sensitivity of consumer savings to consumer electrical storage (ES) and solar PV capacity with AGG_DF (aggDR=100%, conDR=100%), 2050 (Two Degrees+). Source: ESMA.



6.2.8 Summary of section II

In this section we observed the benefits of aggregator-led coordination in overcoming consumer herding by means of deploying algorithm AGG_DF. In 2050 (Two Degrees+) DSM lead to a £1.64 billion reduction in system cost, 0.85MtCO2eq omitted GHG emissions and a 7.5 GW decrease in the annual demand peak. However, we also saw that when aggregators became aggressive in minimising costs, they started to herd (much like consumers) which lead to negative consequences for the grid. Allowing consumers to switch aggregators lead to a further increase in system costs due to uneven distribution of consumer resources between the aggregators. These results are not surprising, since aggregating consumers merely creates larger consumers which compete in the wholesale market.

The only certain solution to overcoming the problem of herding is to involve a central entity, which is able to communicate with the market and inform the stakeholders in the system of the true cost of generating electricity. This is demonstrated by deploying algorithm SO_CM and comparing it to AGG_DF. As suspected, SO_CM lead to slightly higher system savings (especially for the Two Degrees+ scenario in the later years), since the algorithm takes into account system level renewables and communicates these to the market. However, the superiority of algorithm SO_CM over AGG_DF was shown to be marginal revealing certain limitations of the model.

We then explored the impact of billing consumers at fixed tariffs (daily and yearly) rather than at the real time price (RTP). Consumers with solar PV (especially in the domestic sector) were found to be the most vulnerable to the electricity tariff structure, as they rely on exporting electricity. Interestingly, the observations were different for the two national scenarios; whereas in the Steady State consumer with PV saved more with fixed tariffs, in the Two Degrees+ case real-time pricing was more beneficial to these consumers. On the whole, non-flexible consumers benefitted more from fixed tariffs, whereas flexible consumers from RTP. These observations raise an important point regarding allocating the benefits from DSM fairly across different types of consumers. In fact, neither RTP nor flat tariff structure appears to be consistently better across all consumer types and scenarios. This suggests that end-users need to be considered on the individual basis when it comes to allocating costs in the context of DSM.

Finally, through deploying algorithm SO_CM it was revealed that consumer response to the price signal is sensitive to the damping parameter α. When α was set too high relative to the wholesale price level, consumers did not respond much to the price signal, whereas when α was too low consumers overshot when cost minimising. In the next section we discuss the significance of these observations in developing a completely decentralised consumer optimisation regime.

6.3 Part III: Autonomous decentralised consumer DSM - CON_CM+

In the previous section, the benefits of aggregator-led demand side response have been demonstrated by means of deploying algorithm AGG_DF. It was shown that cost minimisation by aggregators can lead to herding (similar to the case when consumers cost minimise autonomously) and how deploying a centrally coordinated DSM regime could help to overcome this problem. Indeed, with algorithm SO_CM (involving the system operator communicating with all stakeholders in the system) savings increased by over £70 million compared to AGG_DF in 2050 Two Degrees+ scenario as a result of the market communicating the true cost of generating power. However, deploying such a DSM regime would require a secure communication infrastructure between consumers, aggregators and the system operator which could be costly. In addition to this, some consumers may not wish to share information about their demand due to privacy concerns.

On the other hand, allowing consumers to cost minimise autonomously can lead to the market herding and as a result compromise on the security of electricity grid (demonstrated in Section 6). Following the observations of how aggregator-led DSM algorithms overcome the issue of consumer herding, in this section algorithm CON_CM (the simplest consumer-led DSM regime) is improved. The new algorithm is then deployed in order to explore the possibility of complete consumer autonomy when performing DSM without compromising the security of the grid.

6.3.1 Developing algorithm CON_CM+

When studying algorithm AGG_DF, it has been observed that it works by suppressing consumer response to the signal received from the aggregator through a damping parameter α, which penalises consumers for deviating from a demand profile in the previous iteration (see step 5 Algorithm 2)). Mathematically, the optimisation function for a consumer c in day d looks like this:

$$\min_{l^c_{net}(t,d)} \sum_{t=1}^{T} l^c_{net}(t,d) \cdot g^k(t,d) + \alpha \cdot (l^c_{net}(t,d) - l^{c,k-1}_{net}(t,d))^2. \tag{6.2}$$

subject to consumer technology constraints specified in Section 3.4.2,

Where, $g^k(t,d)$ is the signal received from the aggregator at time t,

$l^{c,k-1}_{net}(t,d)$ is the net consumer demand from the previous iteration $k-1$ at time t, and

$l^{c,k}_{net}(t,d)$ is the optimal consumer net demand profile obtained in iteration k at time t.

If α is large, the second term in (6.2) becomes more expensive and the consumer does not deviate from the previous net demand profile $l^{c,k-1}_{net}(t,d)$. In contrast if $\alpha = 0$, the consumer ignores the penalty and (6.2) is simplified to:

$$\min \sum_{t=1}^{T} l^c_{net}(t,d) \cdot g^k(t,d), \tag{6.3}$$

which is the same as the optimisation function in algorithm CON_CM with the signal defined as the predicted real time price for electricity, i.e. $g^k(t,d) = p^*(t,d)$.

The default setting for the damping term in algorithm AGG_DF is 0.5 (i.e. $\alpha = 0.5$). Indeed, with a tolerance level of 0.005% the algorithm converges within 15 iterations as expected according to the authors (Gan et al., 2013). However, in algorithm SO_CM (which operates based on the real time price for electricity generation), it has been noticed that the optimal α and the number of iterations required for convergence vary depending on the day. Moreover, with certain values of α algorithm SO_CM achieved significant system cost reductions in just a few iterations. Hence, an optimal value of α must exist where the system would achieve the least cost in just one iteration. This would correspond to a situation when consumers receive a signal from the aggregator, schedule own demand but then do not share new demand information with the system thus preserving their privacy.

Another observation made during the previous analysis was that as a consequence of convergence of algorithm AGG_DF, system demand became smoothed during the course of negotiations between the aggregator and consumers. Yet, demand smoothing is one of the simplest approaches to overcome herding and even now commercially available technologies like Tesla PowerWall are able to do that without the need for an aggregator.

Guided by the above observation, algorithm CON_CM is upgraded into CON_CM+ by introducing a second term into the optimisation function (as demonstrated in Algorithm 5). However, in the proposed algorithm the consumer is penalised for deviating from a flat demand profile rather than the default one (see step 1 in Algorithm 5). This offers a way to combine two coordination strategies for consumer: demand smoothing and cost minimising and to explore the dynamics between them. Moreover, having a flat demand as one of the extremes offers a protective wall from consumers overshooting with cost minimisation.

Algorithm 5: CON_CM+: Autonomous consumer cost minimisation algorithm.

Input : Aggregator a knows predicted day-ahead prices for electricity $p^*(t,d)$. Consumer c knows day-ahead non-deferrable thermal and non-thermal demand profiles $l^c(t,d), q^c(t,d)$, renewable generation $r^c(t,d)$ and technical constraints of own resources.

Output: Consumer net demand profile:

$$l^c_{net}(t,d) \quad \forall t \in [1,T].$$

1 Consumer calculates the average net electricity demand in day d as:

$$< l^c_{net}(d) >= \frac{1}{T}\sum_{t=1}^{T} l^c_{net}(t,d),$$

2 Consumer receives predicted electricity prices $p^*(t,d)$ from the aggregator a and solves the following optimisation problem:

$$\min_{l^c_{net}(t,d)} \sum_{t=1}^{T} l^c_{net}(t,d)\cdot p^*(t,d) + \alpha\cdot(l^c_{net}(t,d) - < l^c_{net}(d) >)^2,$$

subject to consumer technical constraints specified in Appendix C.2.

3 Consumer calculates the final net demand in day d:

$$l^c(t,d) + l^{ch,c}_{ES}(t,d) - l^{dc,c}_{ES}(t,d) + l^c_{HP}(t,d) + l^c_{RH}(t,d) - r^c(t,d),$$

$$\forall t \in [1,T].$$

Figure 6.65: Example of the impact of the damping term α on CON_CM (conDR=100%) coordination for domestic consumer agent of type 3 (with HP, TES), 1st January 2030 (Two Degree scenario). Source: ESMA.

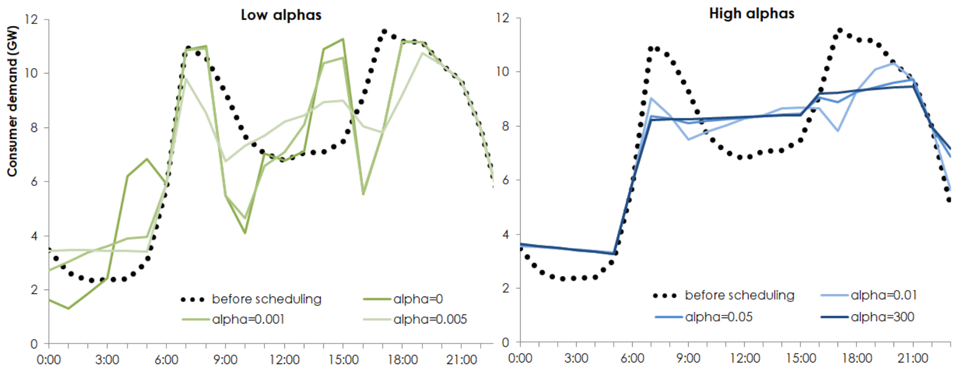


Figure 6.65 shows the impact of α on the net demand profile of consumer. With small values of alpha (i.e. 0, 0.001, 0.005) the demand shifts significantly, whilst for higher values (0.01,0.05) it remains closer to the average flat demand. Hence setting alpha to zero mimics cost minimising behaviour of consumers whilst setting alpha very high (i.e. $\alpha = 300$) mimics a less aggressive consumer strategy of demand smoothing.

It is now of interest to explore how the damping term (α) affects the performance of the system and to find those values which lead to the lowest system cost. As for previous DSM regimes, we vary consumer participation level from 0% to 100% and track system cost for the period 2015-2050 in the Two Degrees+ and Steady State scenarios (Figure 6.66). From the figure we can see that like SO_CM the success of the algorithm in achieving the lowest system cost is sensitive to the choice of the damping parameter α and the consumer participation rate conDR.

The left side of the cost matrices corresponds to pure cost minimising behaviour by consumers. We can see that from 2030 onwards, as consumer participation rate increases to 100% (conDR=100%) the system starts to suffer from herding as indicated by the bright red squares. This is in-line with the observations discussed in Section 6.1 when consumers scheduled based on RTP autonomously (regime CON_CM). However, for certain values of α the system achieves lower system cost compared to the base case (as indicated by the bright blue squares). Moreover, the optimal setting for alpha and conDR varies throughout the year as observed for algorithm SO_CM (Figure 6.67). And so like for SO_CM, the theoretical optimal performance of regime CON_CM+ is evaluated by we selecting those days for which α leads to the least system cost.

6.3.2 Consumer learning algorithm

Thinking of the real world implementation of algorithm CON_CM, it could be a possibility that the central entity informs consumers of the parameter α for day-ahead scheduling. Such a scenario would render a semi-autonomous DSM regime, whereby consumers receive a one way signal from the aggregator but do not send any information back. In order to simulate total consumer autonomy during co-ordination we explore the possibility of consumers (or rather the software on the demand side) learning the parameter α, in which case it become consumer- and day-specific $\alpha^c(d)$.

To do this, a simple reinforcement learning algorithm is deployed, whereby consumer c adjusts $\alpha^c(d)$ depending on the daily cost of electricity $z^c(d)$. Each day consumer compares $z^c(d)$ to the cost of electricity incurred the day before, i.e. $z^c(d-1)$. If the cost of power on the day is higher than in the previous day, i.e. $z^c(d) > z^c(d-1)$, consumer returns α^c to the previous setting, i.e. $\alpha^c(d+1) = \alpha^c(d-1)$. However, if the cost on the day is lower or equal to that on the previous day, i.e. $z^c(d) <= z^c(d-1)$, consumer c does one of two things: explores new strategy by randomly increasing or decreasing α^c by step $conStep$ or keeps α^c at the current setting, i.e. $\alpha^c(d+1) = \alpha^c(d)$. The amount of the time consumer explores new strategies is defined by a parameter *conExplore*, which together with $conStep$ is set at the system level. At the end of the day consumer c updates the previous values for daily cost and the damping parameter, i.e. $z^c(d-1) = z^c(d)$ and $\alpha^c(d-1) = \alpha^c(d)$.

Figure 6.66: Annual system costs with CON_CM (varying α and conDR settings), 2015-2050. Source: ESMA.

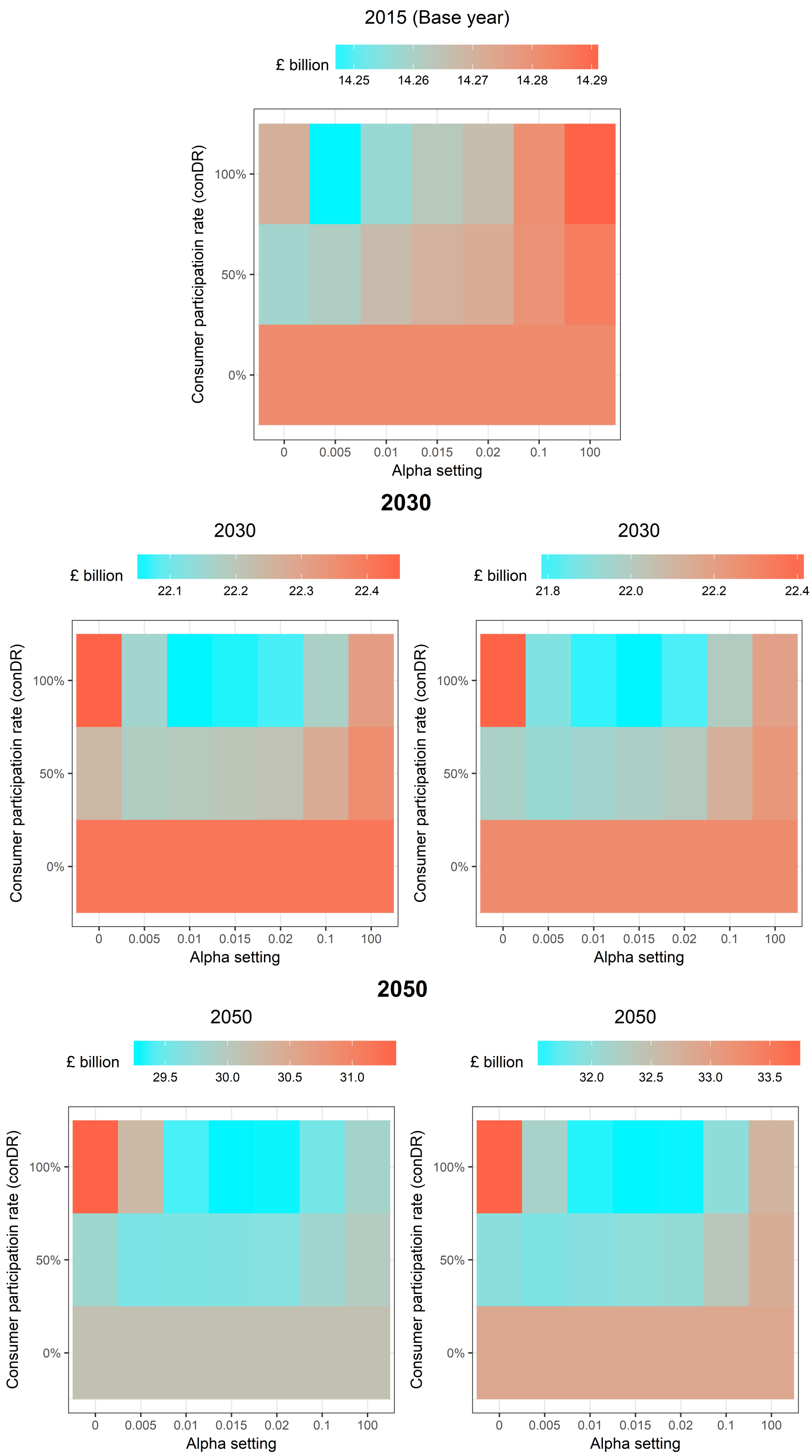


Figure 6.67: Alpha setting (α) selected on the basis of least daily system cost with CON_CM+ (conDR=100%), 2015-2050. Source: ESMA.

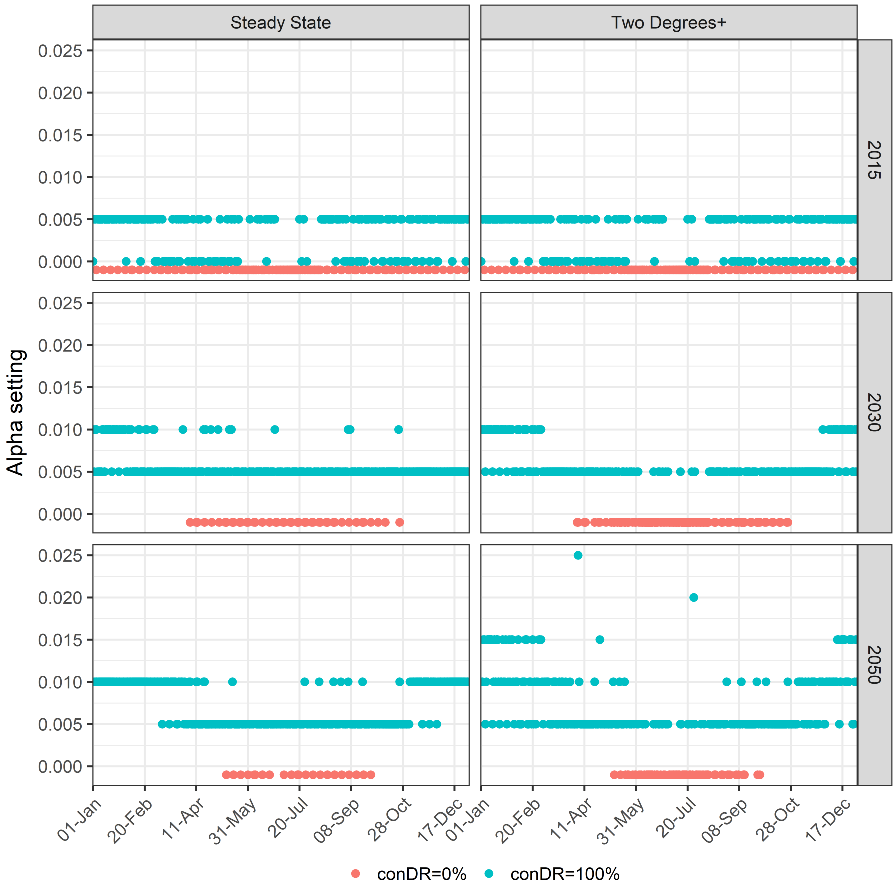
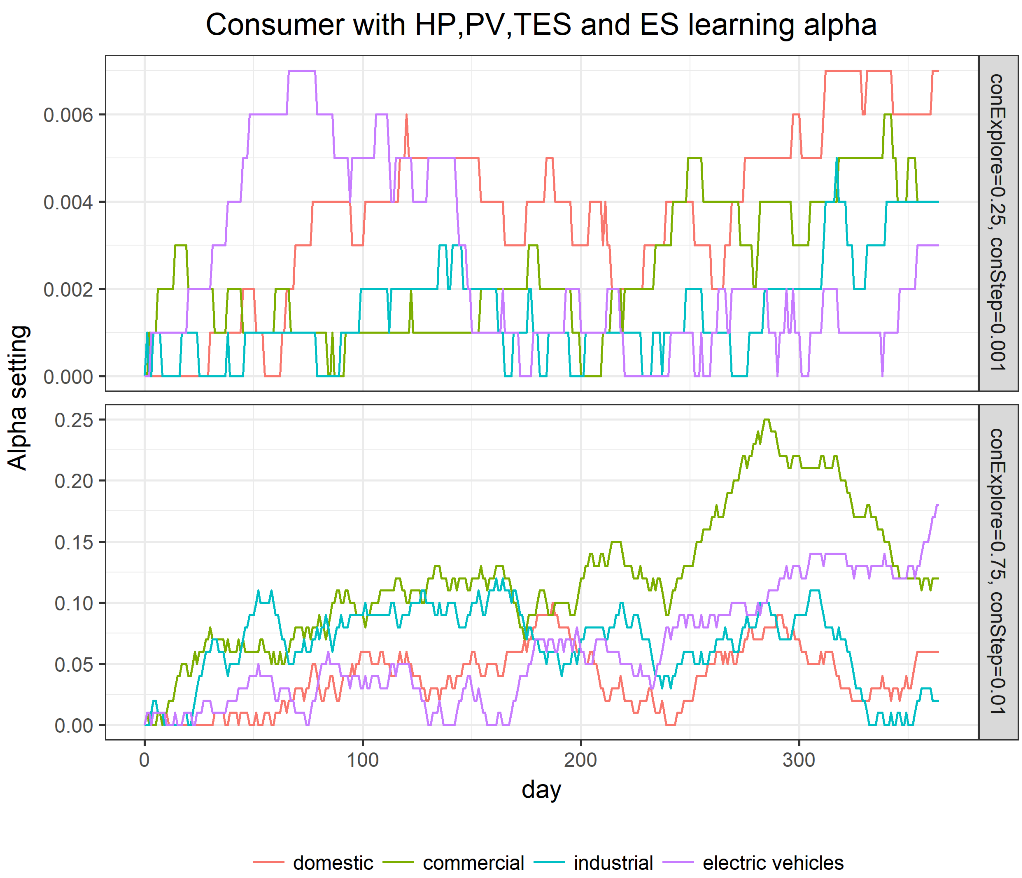


Figure E.15 demonstrates the learning algorithm under different sets of parameters in 2050 Two Degrees+. It is possible to see that with a larger step size (conStep) and exploration parameter (conExplore) consumer damping term α^c fluctuates much more than when conExplore and conStep are small. Needless to say the choice of parameters conExplore and conStep will also affect the system cost, and so sensitivity analysis is performed in order to find the combination of parameters which leads to the best consumer learning strategy (see Appendix E.3).

Following the calibration procedure (where conExplore and conStep have been set to 0.5 and 0.005 respectively), the simulation is re-run with CON_CM+ with consumer learning, i.e. CON_CM+(LEARN), and compare all DSM regimes in the next section.

Figure 6.68: Demonstration of the α learning algorithm for consumers of type 9 (with HP,PV,TES and ES) and electric vehicles, 2050 (Two Degrees+). Source: ESMA.



6.3.3 Comparison of all DSM regimes

Figures 6.69-6.71 demonstrate how the four DSM regimes considered in this work compare in terms of total system cost, GHG emissions and demand peaks. In terms of total system savings, regime SO_CM achieves the best performance (£1.71 billion) followed by AGG_DF (£1.64 billion), CON_CM+ (£1.4 billion), and CON_CM+(LEARN)(£1.24 billion) in 2050 (Two Degrees+). We note that regime CON_CM+ achieves higher system savings compared to CON_CM+(LEARN), which is expected since in CON_CM+ α is set centrally.

Looking at Figure 6.70, we can see that prior to 2030 lowest system cost does not necessarily translate into lowest GHG emissions. Hence in 2015, CON_CM+ performs better than SO_CM and AGG_DF.

Figure 6.69: Annual system savings with CON_CM+(LEARN), CON_CM+, AGG_DF and SO_CM relative to the base case, 2015-2050. Source: ESMA.

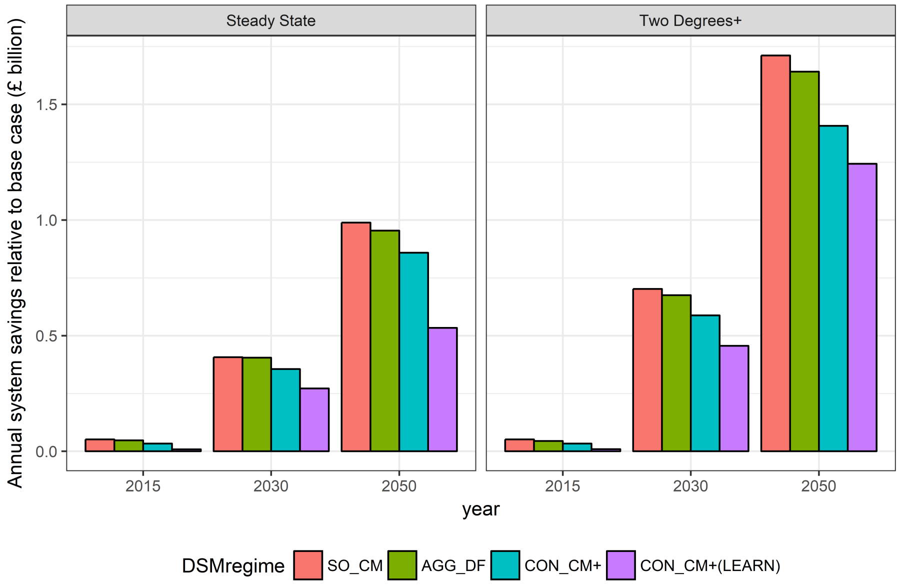
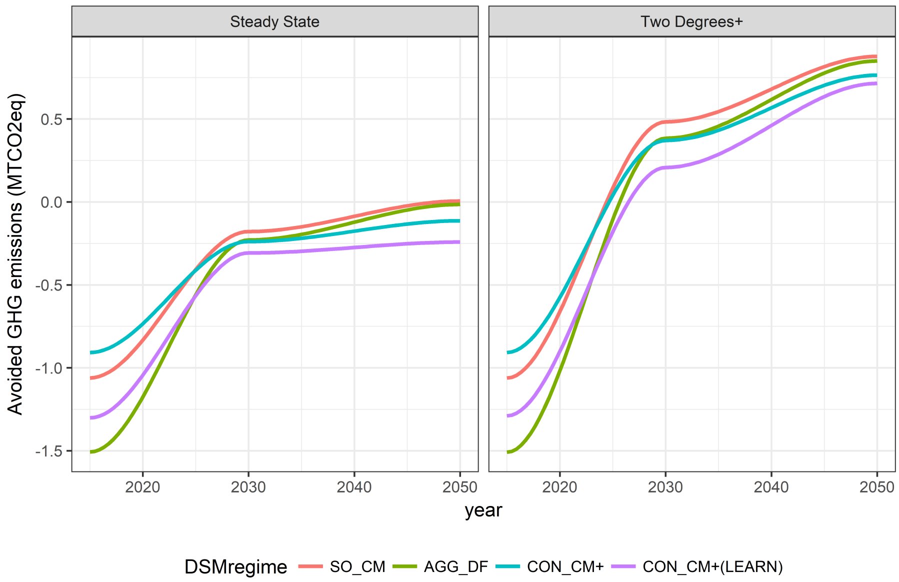


Figure 6.70: Avoided GHG emissions with CON_CM+(LEARN), CON_CM+, AGG_DF and SO_CM, 2015-2050. Source: ESMA.



This is because prior to 2030 carbon prices are relatively low and so the system chooses to run the more polluting cheaper generators. Post 2030, regime SO_CM consistently achieves the highest level of avoided GHG emissions suggesting a better alignment between the cost and sustainability of the electricity grid. However, the improvements are marginal compared to algorithm AGG_DF which does not take account of system level renewables. It is suspected that this is because the model does not include the cost of curtailing renewables, nor does it take into account how the efficiency of dispatchable generators is affected by their ramping rate. Hence, the cost of cycling generators is underestimated leading to an overestimation of the use of renewables.

For 2030-2050 across both national scenarios, regimes AGG_DF and SO_CM achieve the lowest system demand peaks. Apart from 2015, regime CON_CM+(LEARN) consistently leads to the highest level of system demand peaks across all years and scenarios. This happens because with CON_CM+(LEARN) consumers are continuously adjusting the damping term α^c - a parameter towards which the system is very sensitive. As consumers explore the parameter α^c, situations exist where they overshoot and demonstrate the symptoms of herding which leads to increased demand peaks.

Figure 6.71: Annual system demand peaks with CON_CM+(LEARN), CON_CM+, AGG_DF and SO_CM, 2015-2050. Source: ESMA.

Analysis of consumer savings across all DSM regimes shows that on the whole end-users save more under centralised approached (i.e. SO_CM and AGG_DF), suggesting that consumers benefit together with the system (Figure 6.72). However, we observe that for non-flexible consumers with PV decentralised approaches (i.e. CON_CM+ and CON_CM+(LEARN)) outperform centralised DSM, especially in the Steady State scenario (Figure 6.73).

Figure 6.72: Change in the price of electricity for consumers with a heat pump (HP) and thermal energy storage (TES) with different DSM regimes calculated at RTP in 2050. Source: ESMA

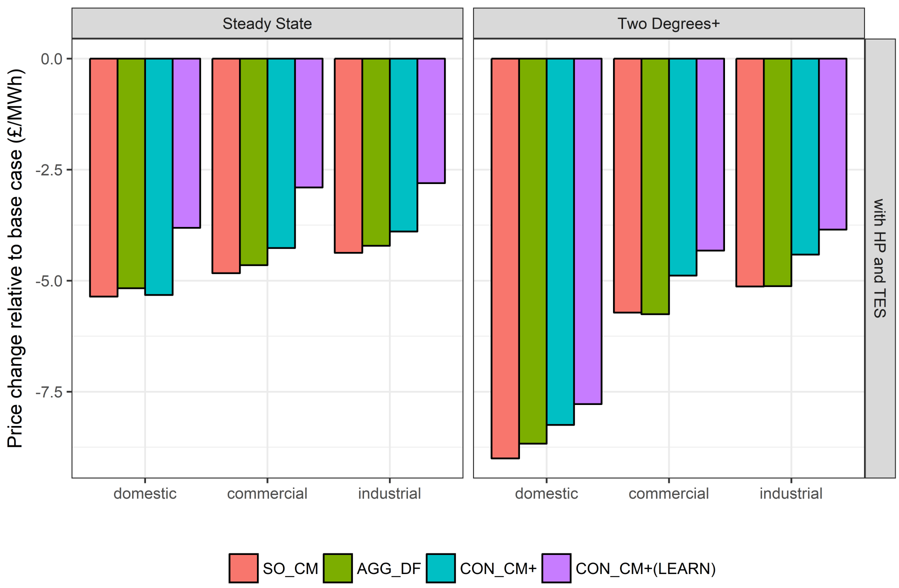
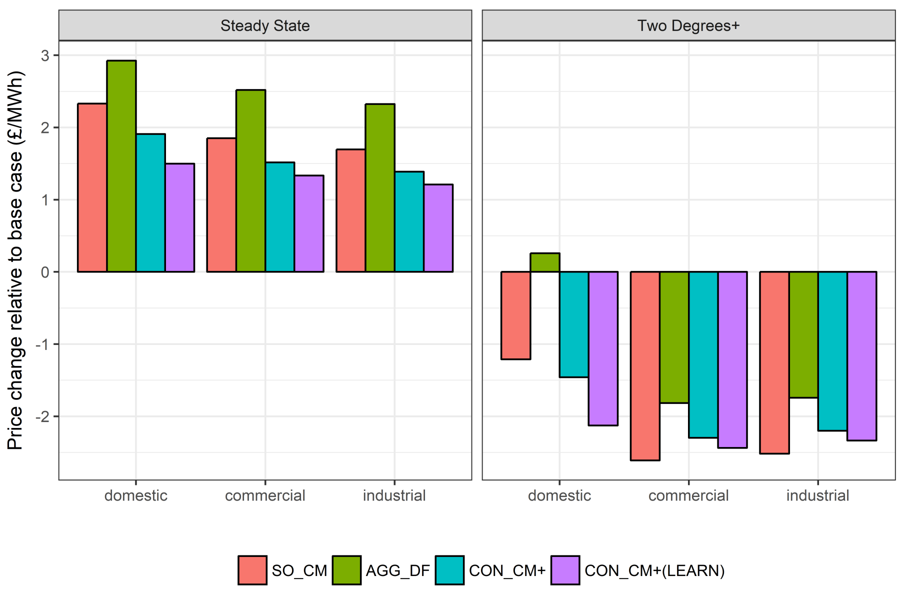


Figure 6.73: Change in the price of electricity for consumers with solar PV under different DSM regimes calculated at RTP. Source: ESMA



In the Two Degrees+ scenario domestic consumers with solar PV save more when the market is completely autonomous under CON_CM+(LEARN). On the contrary, regime AGG_DF performs the worst for these consumers in both Steady State and Two Degrees+ scenarios. This is because consumers with solar PV rely on exporting electricity at the higher prices and demand smoothing under AGG_DF reduces the arbitrage opportunity for them. Of course how much different consumers pay depends very much on the structure of the tariff (as we have seen when considering fixed prices). However, by comparing different regimes it was possible to identify (once again) that conflict of interest exists between certain types of consumers and the system.

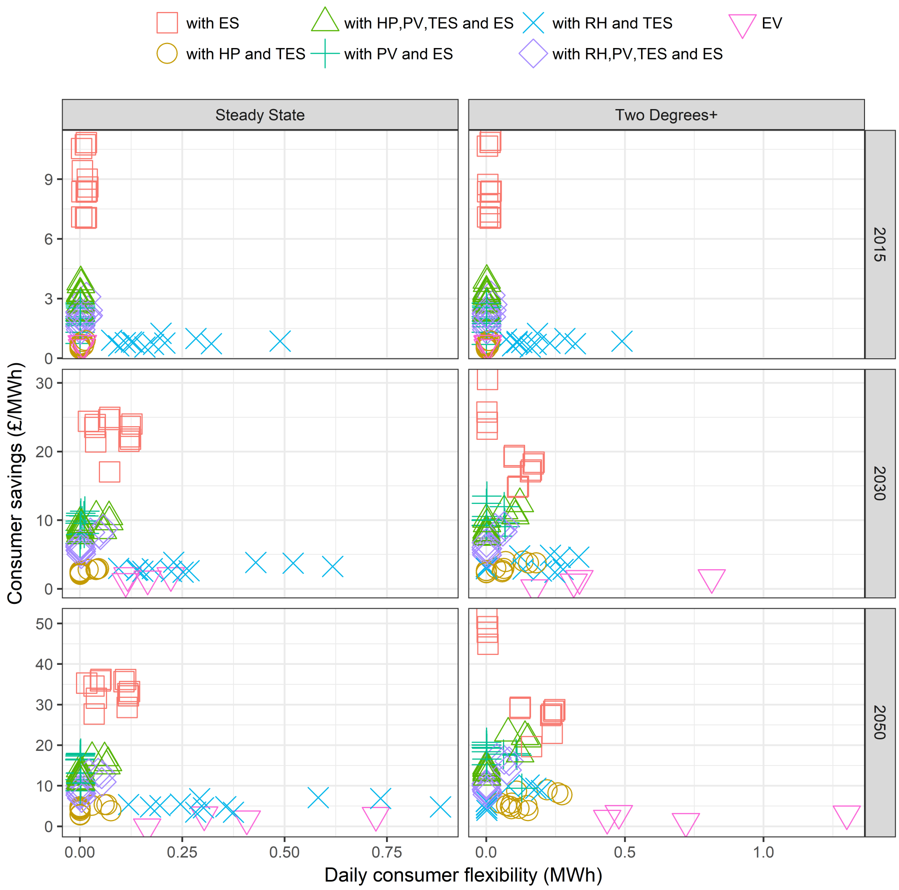
6.3.4 How should consumer flexibility be rewarded?

Thinking of the service consumers provide to the grid when shifting demand, it would seem fair that their reward is based on the amount of flexibility they offer to the grid. In order to assess whether that is the case, consumer flexibility is calculated as the absolute change in the residual demand profile before and after DSM (averaged per day) and plotted against annual savings per unit of energy consumed (£/MWh) calculated at RTP (Figure 6.74).

From the figure we can see that consumer savings depend very much on the type of resources they possess. Firstly, we notice that electric vehicles and consumers with resistance heaters and thermal energy storage (i.e. with RH and TES) see the lowest savings relative to the amount of flexibility they offer, in particular in the Steady State scenario. On the other hand consumers with electrical storage see the highest savings relative to the amount of offered flexibility to the grid. This is because consumers with electrical heating and TES are constrained by the thermal demand pattern they have to fulfil. This allows consumers without electric heating to be more effective when shifting demand, which leads to larger savings. These observations suggest that demand pattern plays as much of a role in determining consumer benefits from DSM as the amount of flexibility one can offer.

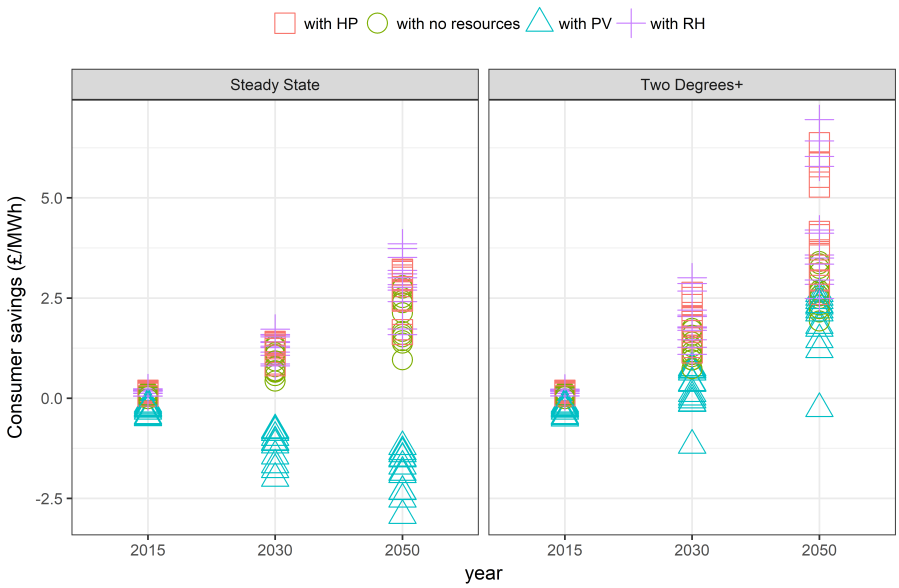
Finally, non-flexible consumers are also impacted by DSM albeit not being able to shift demand at all (Figure 6.75). Out of those, consumers with electric

Figure 6.74: Change in the price of electricity for flexible consumers with different resources under SO_CM (conDR=100%, aggDR=100%) in 2050. Source: ESMA



heating end up benefitting the most whereby those with solar PV lose out for reasons discussed earlier sections. However, at under £1/kWh the impact is marginal compared to that of flexible consumers. Nevertheless, whether they want it or not some inflexible consumers save whilst others loose out making it an important point to consider when thinking of the future tariff structure for retail electricity.

Figure 6.75: Change in the price of electricity for non-flexible consumers with different resources across all DSM regimes calculated at RTP in 2050. Source: ESMA



6.3.5 Summary of part III

In part three of the results chapter, we explored the possibility of autonomous consumer coordination by developing algorithm CON_CM+, which combined consumer strategies for demand smoothing and cost minimisation based on RTP. The algorithm works by penalising consumers for deviating from a smooth demand profile by a damping term α thereby supressing consumer herding. It has been demonstrated that like algorithm SO_CM, CON_CM+ is sensitive to the choice of α and in order to make it truly autonomous a simple learning algorithm was introduced which allowed consumers to adjust the parameter themselves.

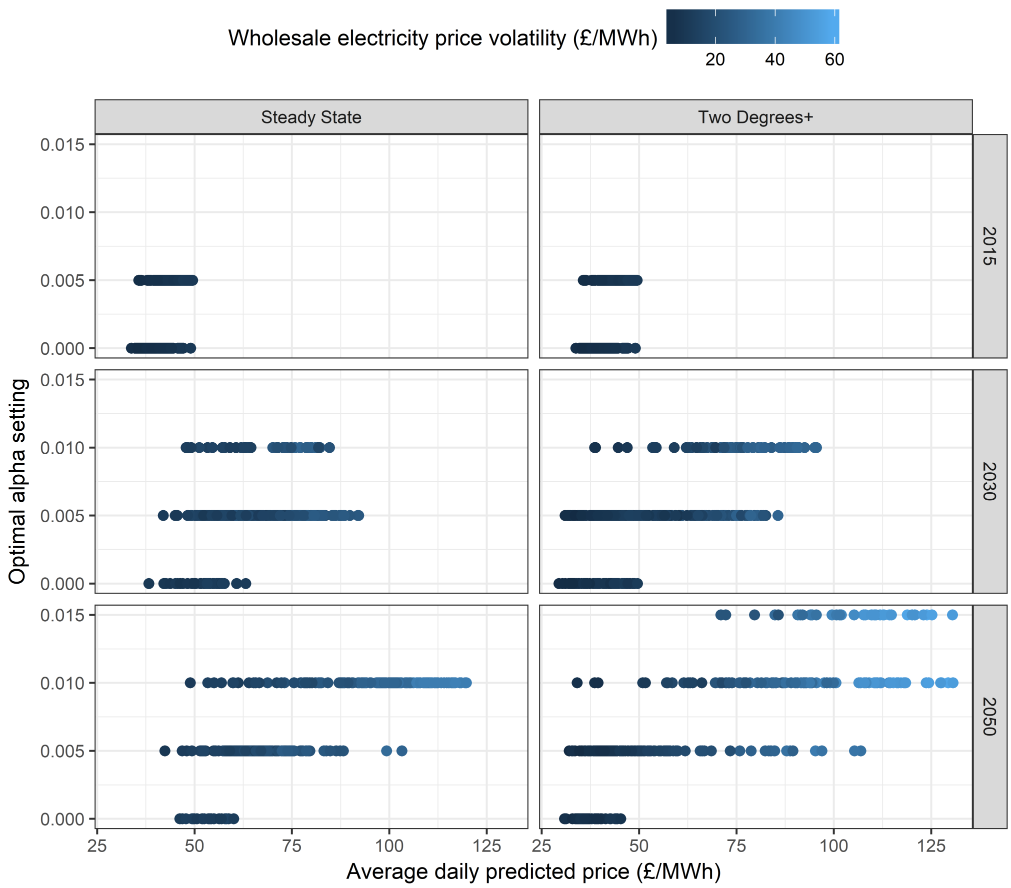
In terms of system benefits, it is concluded that algorithm SO_CM achieves the best performance, followed closely by AGG_DF. In terms of consumer savings, for most types centralised coordination was observed to be more beneficial, i.e. regimes SO_CM and AGG_DF. However, it was demonstrated that for non-flexible consumers with solar PV decentralised DSM regimes (i.e. CON_CM+ and CON_CM (LEARN)) lead to higher savings.

To summarise, we observed a trade-off between stakeholder autonomy and system optimality, i.e. the system performed best with SO_CM however that involved consumers giving up information about their flexibility. It is argued that consumer control can be minimised through an algorithm such as CON_CM+, whereby the information flow between consumers and the system is limited. It is noted that the algorithm for consumer adjusting α^c described here is very simplistic and with its improvement autonomous coordination could be a lot more successful. More importantly, it was demonstrated that in the context of the simulation framework, consumers (or rather the software which controls their demand) is able to learn the behaviour by slowly reacting to the market. Of course, this does not go without some trial and error as the end-users adapt their behaviour which can end-up costing the system as has been demonstrated in this section.

We finished the chapter by demonstrating consumer benefits relative to the flexibility they can offer to the fgrid. Although more flexibility leads to more savings, the relationship isn't linear and consumer demand pattern plays an important role in determining how much each individual consumer profits from DSM. It is noted that consumers with ES get the highest benefits relative to the amount of flexibility they provide to the grid in contrast to those with electric heating and thermal storage. This has much to do with the efficiency of the storage and consumer demand constraints. Finally, it has been shown that non-flexible consumers (which have no impact of system level demand) experience different benefits from DSM, especially those with solar PV which are very vulnerable to the export price of electricity. These results demonstrated that the retail electricity tariff structure is critical to ensuring a fair allocation of costs and benefits to consumers in the context of DSM.

A note on centrally setting α. Figure 6.76 shows a plot of optimal values of α versus the average level of predicted prices used by consumers in algorithm CON_CM+ across all years and scenarios. It is possible to see that α is influenced by the mean as well as the volatility of the daily wholesale electricity prices as demonstrated by the changing shade of the data points in the chart - higher volatility means higher α. Now, this result is not surprising since in the original optimisation formula (6.2) the damping term is counter acting the predicted price $p^*(t,d)$ and as the price level increases then so must the damping parameter. Otherwise, the first term in (6.2) outweighs α and consumers start to herd when cost minimising. This observation suggests that the system would be able to learn the optimal α to choose to send to consumers and can act as a tool for improving algorithms SO_CM and CON_CM+. Even in the case when consumers learn, i.e. CON_CM+(LEARN) the system could still send a suggested initial α to set a boundary for consumer α range.

Figure 6.76: Average daily price plotted against optimal alpha setting for CON_CM+ (conDR=100%) in the Steady State and Two Degrees+ scenarios, 2015-2050.



Chapter 7

Conclusions

In light with increasing penetration of renewable energy sources, demand side management (DSM) has been receiving a lot of attention from industry and academia as a promising solution to balancing electricity in the grid. Yet, the implications of DSM being deployed by multiple stakeholders each with their varying objectives, have not been fully understood. For example, one of the most popular and simplest approached to DSM is to inform consumers of the real time price (RTP) for electricity, allowing them to shift demand to off-peak hours. However, with high enough end-user flexibility such behaviour can lead to consumers herding towards the same periods of low electricity prices. This can result in more volatile system demand and higher costs, as a result of the market adjusting to chaotic consumer behaviour.

Aggregators can help alleviate the problem of consumer herding by coordinating the demand of a group of end-users. However, aggregators can themselves herd as they compete in the wholesale market for cheap electricity and larger consumer market share. Moreover, consumer switching between aggregators can aggravate this issue, as end-user resources migrate between different aggregators. The only sure way to optimise system demand is through a centrally controlled DSM, which would keep track of the real time cost for generating electricity. However, this would require consumers to share some information on their electricity demand patterns or flexibility - something that might not be appreciated by some due to privacy concerns. Finally, it is uncertain how different types of consumers (i.e. those with and without flexible resources) might be affected by the deployment of DSM.

The objective set out for this work was to evaluate the potential opportunities and challenges when demand side management (DSM) is used as a tool for balancing electricity supply and demand by different stakeholders in the grid. In order to do this holistically and address the gaps identified in existing research, a bespoke model for electricity system management using an agent based approach (ESMA) has been built taking Great Britain as a case study. Three types of stakeholders have been identified in the grid which are able to perform DSM: consumers, aggregators and the system operator (SO). The model considers ten types of consumers (depending on the combination of resources they possess) within four economic sectors (domestic, commercial, industrial and transportation). The aggregator layer represents entities which are able to pool consumers together and instruct them on how to shift demand. At the top layer, the SO oversees the whole system and communicates electricity demand to the market agent, which dispatches electricity generation units and calculates the prices for electricity. Guided by the scenarios provided by the National Grid, two cases for the evolution of the British electricity system have been considered for the period of 2015-2050: Steady State (least flexible and renewable system) and Two Degrees+ (the most flexible and renewable system). For each of the national scenarios the long term impact of the different DSM regimes has been assessed, by monitoring system costs, greenhouse gas emissions, and consumer bills.

Through building ESMA and exploring different national scenarios and DSM regimes, the aim was to come up with market rules which would minimise the risks and maximise the benefits of DSM. In order to achieve this, the following research questions have been posed at the beginning of this work:

1. Up to which point is autonomous consumer cost minimisation based on the real time price effective in reducing system costs and greenhouse gas emissions?

2. How can aggregators facilitate effective demand side management and what potential risks might they bring along?

3. What is the appropriate tariff structure for rewarding consumer flexibility?

4. Is it possible for consumers to schedule demand autonomously without compromising the stability and sustainability of the electricity system?

7.1 Recap of key results

In part one of the results, we addressed the first research question by investigating the limits of the simplest form of DSM, whereby consumers autonomously cost minimise based on the real time price of electricity. The simulation results demonstrated that in the early scenario years (when consumer flexibility and renewable capacity were low), communicating RTP to consumers led to system savings as renewable resources were better utilised. In the base year 2015, total system savings amounted to £2.3 million when 50% of end-users cost minimised and £1.1 million at 100% end-user participation in DSM. However, with high consumer flexibility in the later years (especially in the Two Degrees+ scenario), the system started to suffer from herding. When all consumers cost minimised based on RTP, the system experienced losses from 2020 onwards in both Steady State and Two Degrees+ scenarios. In 2050 (Steady State) system cost increased by £1.2 billion, whilst GHG emissions went up by 1,266 MtCO2eq per year relative to the base case (without DSM). As a result of the elevated wholesale prices for electricity, flexible consumers saw their bills go up (especially those with solar PV and electrical storage). Yet, inflexible consumer (not being able to shift demand) profited in these conditions as they bought electricity at the lowest prices when the rest of the market herded. These observations highlight a potential conflict of interest between inflexible consumers and the system. From performing the sensitivity analysis, it was found that herding can be controlled through consumer export prices for electricity. The simulation results demonstrated that the system losses can be minimised when the export price was reduced relative to the import price of electricity. This happened because consumers favoured self-consumption and did not over-export electricity to the grid, which reduced the curtailment of system level renewables. It was also observed that when the SO predicted the future electricity demand, putting more weight to past data lead to the prices becoming more chaotic as consumer shifted day-to-day consumption in order to cost minimise. Hence, controlling wholesale price from becoming too volatile can act as another tool for stabilising system demand and prices during DSM.

In part two of the results, we addressed the second research question by demonstrating the benefits of a well-coordinated aggregator-led DSM. In contrast to part one, it was observed that flexible consumers benefitted much more from the deployment of DSM compared to inflexible consumers. We then explored billing end-users at fixed daily and yearly tariffs and compared the reductions in consumer bills to the case with RTP. It was found that inflexible consumers with solar PV were most vulnerable to the tariff structure and that neither RTP nor fixed tariffs were better across all scenarios and years in terms of allocating the benefits from DSM across different consumer types. Overall, results demonstrated that fixed tariffs lead to more modest savings for flexible consumers compared to non-flexible consumers, since the shape of the demand curve played less of a role in this case. This analysis suggested that different types of end-users need to be addressed on the individual basis when determining the benefits from DSM.

It was then demonstrated that aggregator herding is possible when aggregators became more aggressive in their objective to cost minimise. Moreover, consumer switching between aggregators made the situation worse as end-user resources were shared unevenly between the aggregators leading to a more chaotic electricity market. Finally, the superiority of a centrally coordinated DSM was demonstrated which addressed research question three. Total system saving reached £1.7 billion in 2050 (Two Degrees+) - £70 million more than in the case when the SO was not involved. These observations suggest that the true value of aggregators is in communicating the information between the system and the consumers. However, this scenario removes the natural competition between the aggregators in addition to raising the question regarding the allocation of benefits to different stakeholders involved.

In part three of the results, we investigated the topic of consumer autonomy in the context of DSM through developing a new algorithm for consumer demand scheduling. The algorithm evolved as a product of the observation made during the first two sections of the analysis. When comparing all DSM regimes considered in this work, it was found that the most centralised approach lead to the highest system and consumer savings and lowest GHG emissions, suggesting a trade-off between system optimality and consumer autonomy. This result echoes the concept referred to by economists as the *price of anarchy*, whereby the efficiency of the system degrades when the players start to behave selfishly (Koutsoupias and Srinivasan, 2009). That said, for certain types of end-users (i.e. those with solar PV) a more decentralised DSM approach lead to higher savings highlighting a source of conflict of interest between certain consumers and the system.

The results chapter was concluded by a discussion on the mechanism for rewarding consumers for their flexibility. It was demonstrated that consumers with different resources benefitted from a varying degree of savings when offering the same amount of flexibility to the grid. For example, those with electric heating and electrical storage saw much lower marginal savings from DSM compared to those with electrical storage only. Hence, end-user demand pattern played as much of a role in determining consumer benefits from DSM as their flexibility.

7.2 Main messages

Going back to the research questions posed at the beginning of this work, the answers are summarised as follows:

1. In the earlier years of the simulation (or when system flexibility and renewable capacity are low), communicating the real-time price of electricity to end-users can be an effective solution to managing electricity consumption and optimising the use of renewable generation in the grid. However, going past 2020 and further into the future it is possible that consumer herding could harm the grid leading to increased system costs and greenhouse gas emissions. Moreover, it is flexible consumers who end up paying for herding whereas those without any resources save. This might deter certain con-

sumers from purchasing storage and participating in DSM, which is counter-productive to the government goals of engaging the end-user and promoting system flexibility.

2. Aggregator-led coordination can help overcome the issue of consumer herding but only when they are communicated the information on the true cost of generating electricity. Otherwise, aggregators can herd much like consumers leading to increased system costs and GHG emissions. Hence, the true value of aggregators is in communicating system level information to consumers and assisting a central entity (such as the System Operator) in balancing the grid.

3. Autonomous consumer DSM is possible, however it is likely to emerge from a more centralised regime giving consumers (and their gadgets) the opportunity to learn the right signals when adjusting to the market. In the context of the real world implementation of such a regime, this translates into the consumer demand scheduling software acquiring starter learning information from previous market observations. This would ensure a safe transition to purely decentralised DSM. It is argued that the amount of information required from consumers in the initial stages of such transition can be limited to one-way signalling from the grid to end-users thus alleviating consumer privacy concerns.

4. In order to extract maximum benefit from consumer flexibility, the future tariffs for electricity need to reflect the services provided by end-users in the context of DSM. According to the simulation, consumer tariffs based purely on RTP or fixed price for electricity are inappropriate for fairly rewarding end-user services. This is especially applicable to consumers with renewable generation resources who rely on exporting power into the grid. Hence, a more tailor-made approach is required when coming up with tariff structures for different types of consumers.

7.3 Model limitations and further work

When creating the modelling framework ESMA and obtaining data for the simulation scenarios, a number of assumptions have been made. Some of the model limitations have been discussed throughout the document. This chapter covers the most significant limitations and offers ways to improve the model.

1. **Electricity generation.** In modelling the electricity generation market, capital costs of different generation technologies are ignored since the purpose of this work is to explore DSM dynamics and control using short run avoidable costs. In addition to this, generators are grouped based on their technology, i.e. 9 real world coal power plants with an average capacity of 1.6GW are represented by one coal generator of capacity 15GW. As a consequence, the technical characteristics are assumed to be the same for all generators of the same type. Moreover, technical characteristics of generators stay fixed throughout the simulation period. Hence, if in 2015 the variable O&M cost has been assumed at £2.09/MWh and efficiency at 50% then the same is true in 2050. This significantly simplifies the market dynamics, since in reality power generators of the same technology vary in their characteristic depending on the year they were built, the type of fuel they use, their size, and their operation schedule (especially significant for efficiency). As a result of these simplifications, the model underestimates the cost of electricity, since instead of dispatching nine different generators it dispatches one nine times the size. In order to improve the model, it would be necessary to reflect individual generator characteristics such as capital and operational costs, efficiency, carbon emission factor, and generator outages.

2. **Wholesale electricity market.** The wholesale electricity market is approximated as a one-shot day-ahead market followed by a rescheduling in the balancing market. In reality, contracts for physical delivery of electricity range from years to seconds ahead depending on the type of product being sold. As a consequence of this approximation, the model underestimates the value of DSM, which is especially valuable in the balancing market. Although a

limitation, it is argued that the day-ahead market captures sufficient market dynamics to effectively model the relationship between electricity demand and prices. Including a more representative balancing market would better reflect the value of demand side management.

3. **Network constraints.** Network constraints are not modelled, which means that electricity can flow freely between the points of generation and consumption. This underestimates the cost of electricity since the price of electricity also includes the cost of utilising the grid. Another consequence of omitting the network constraints is that the impact of DSM at the local level is not evaluated. To elaborate, when consumers are coordinated centrally at the transmission level the demand is optimised, however at lower voltages the constraints might be breached. This is an important point not being addressed in the research - conflict of interest when managing demand at the transmission and distribution levels. However, by removing the network constraints it is possible to assess the maximum impact of DSM, both positive and negative. Including network constraints would reflect the value of DSM more accurately.

4. **Model uncertainty.** Apart from the case when consumers are randomly selected to switch aggregators, the model is deterministic. On the supply side, it is assumed that there is no error in predicting renewable supply and operation of dispatchable generation. This assumption is justified by the continuous improvements in renewable generation forecasting models. On the demand side, it is assumed that there is no error in predicting non-deferrable consumer demand. This comes from an assumption that human behaviour is unlikely to significantly change in the future. Hence, from the system's point of view the only source of uncertainty on the demand side comes from the consumers reacting to the aggregator DSM signals. These assumptions lead to an underestimation of system costs and therefore impact of DSM. Integrating uncertainty in predicting renewable supply, as well as non-deferrable consumer demand would reflect the impact of DSM more accurately.

5. **Fuel prices.** The wholesale prices for primary fuels (gas, coal, oil, nuclear, biomass) are modelled on an annual basis, meaning that there are no daily and hourly fluctuations. This leads to more static costs for generating electricity by different types of generators. As has been demonstrated in the chapter on validation, this can lead to the system incorrectly picking generation technologies when solving the dispatch optimisation model. However, considering the level of uncertainty in predicting the future it is argued that considering two boundary scenarios which span a range of potential cases for the evolution of the national grid (including prices) is sufficient to answering our research questions. An improvement to the model would be to include more dynamic fuel prices, which would better reflect the true cost of generating electricity.

6. **Consumer demand profiles.** Although the uptake of consumer technologies is explicitly considered in the model, it is assumed that the shape of non-deferrable consumer demand will stay the same throughout the simulation period. In the case of domestic consumers this might be the case (i.e. watching TV and cooking), however for non-domestic consumers (especially industrial) it is difficult to predict how the demand will change over the years. The main consequence of this assumption is on the shape of the system demand curve and system prices. An improvement to the model would be to consider a social angle on how end-users might utilise energy in the future. However, it is an ambitious improvement which would significantly complicate the model. Moreover, the objective of this work to evaluate the potential impact of DSM on the system and consumers, can be achieved without such detailed focus on how the shape of the consumer demand curve will change in the future.

7. **District heating.** District heating is not considered in the model, however it constitutes an important part of the British electricity system. Moreover, district heating can act as a good source of energy storage and as an aggregator unit for end-users. By not including the district heating network all of the power to schedule demand falls onto consumers themselves, which is

likely to overestimate to potential for consumer herding. However, this way of modelling the system offers a way to consider the extremes for the future evolution of the grid. Including district heating would provide a more holistic representation of the electricity grid and potential for DSM.

7.4 Addressing model limitations in ESMA

In order to address the limitations which impact the correct calculations of system cost, an uplift was introduced which allowed to calibrate the electricity prices against historical and (to an extent) future values. However, the data against which the prices were calibrated was limited. In the case of historical data, this was because for over-the-counter market (which represents the majority of electricity contracts for physical delivery) this data was not available. In the case of future prices, only average annual values were available and so it was necessary to make do with calibrating against average annual electricity prices offered by the National Grid. The major consequence of the limitations described above is that that in terms of system costs and GHG emissions the impact of DSM is underestimated.

The second tool used for addressing limitations was sensitivity analysis. For example, consumer solar PV and storage capacity was varied in order to address how these parameters affect the impact of DSM on different types of consumers as well as the system. For the same reason the weight to past prices used when the System Operator predicts day-ahead demand was varied around the default value. Modelling two boundary scenarios (Two Degrees+ and Steady State) was the main solution to addressing limitations concerning the data in the model. With regarding to the future electricity tariffs, dynamic and static prices were explored.

Appendix A

Data preparation

The following chapter describes the methods involved in data preparation and model calibration as well, as going over certain methods which are not mentioned in the main body of the thesis.

A.1 Consumer electricity demand profiles

For each consumer c, electricity demand profiles can split into two components: weather independent consumption, $l^c(t,d)$ (due to cooking and watching TV) and weather dependent component (water and space heating), which is achieved through operating the heat pump or a resistance heating, $l^c_{HP}(t,d)$ and $l^c_{RH}(t,d)$. Weather dependent demand is defined as 'thermal' and weather independent demand as 'non-thermal' and will refer to them accordingly from now on.

In the following section we describe the process of obtaining consumer demand profiles making a distinction between stationary sectors (domestic, commercial, industrial) and transport, since preparing data for transportation sector requires a slightly different procedure.

A.1.1 Stationary sectors (domestic, commercial, industrial)

The main datasets used to obtain hourly electricity demand profiles for stationary sectors are the standard half-hourly demand profiles offered by Elexon (Elexon, 2017a). Elexon provides demand data for 8 consumer classes defined as follows:

1. **Profile Class 1** – Domestic Unrestricted Customers

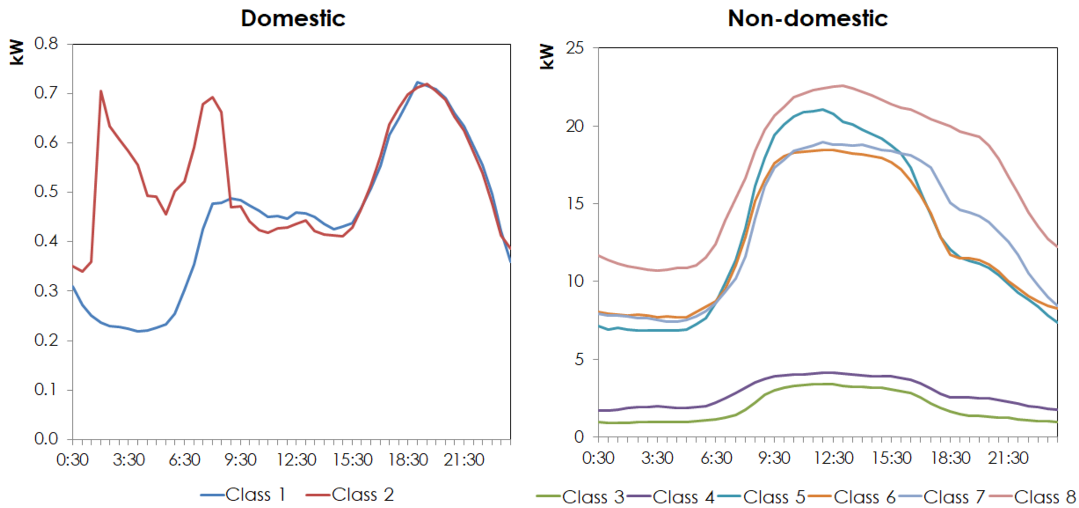
2. **Profile Class 2** – Domestic Economy 7 Customers
3. **Profile Class 3** – Non-Domestic Unrestricted Customers
4. **Profile Class 4** – Non-Domestic Economy 7 Customers
5. **Profile Class 5** – Non-Domestic Maximum Demand Customers with a Peak Load Factor of less than 20%
6. **Profile Class 6** – Non-Domestic Maximum Demand Customers with a Peak Load Factor between 20% and 30%
7. **Profile Class 7** – Non-Domestic Maximum Demand Customers with a Peak Load Factor between 30% and 40%
8. **Profile Class 8** – Non-Domestic Maximum Demand Customers with a Peak Load Factor over 40%

For each of the 8 consumer types, Elexon provides demand profiles for five different seasons (Winter, Spring, Summer, High Summer and Autumn) and three day types (weekday, Saturday and Sunday), which enables us to compile an annual half-hourly demand profile for eight types of consumers. Figure A.1 shows half-hourly electricity consumption by domestic and non-domestic consumers during an average autumn weekday, highlighting the difference in their pattern and magnitude. On the left side, it is possible to see two domestic profiles: one with off-peak electric heating (in red) and one without (in blue). Since thermal consumption is modelled explicitly, profiles of class 2 are not considered.

For non-domestic sectors, profiles across the relevant consumer classes are averaged, i.e. class 3 and 4 for commercial and classes 5, 6, 7 and 8 for industrial sectors. This renders three types of non-deferrable electricity demand profiles representing domestic, commercial and industrial consumers, $l^{dom}(t,d), l^{com}(t,d), l^{ind}(t,d)$ where t stands for the hour and d for the day of the simulation.

A note on notation. When the superscript includes the economic sector (i.e. $l^{dom}(t,d)$), the variable represents individual real life consumer, whereas when the superscript includes the consumer index (i.e. $l^{c}(t,d)$) the variable corresponds to a modelled consumer agent, which represents a pool of individual consumers of the same type (see section 3.4.2.1 on agent representation).

Figure A.1: Half-hourly electricity demand profiles for non-domestic consumers for an average autumn weekday.



A.1.1.1 Non-thermal consumer demand profiles

In order to obtain non-thermal consumer demand, the total consumer demand profiles, $l^{dom}_{tot}(t,d), l^{com}_{tot}(t,d), l^{ind}_{tot}(t,d)$, are stripped off the thermal component. In order to do that the following assumptions are made:

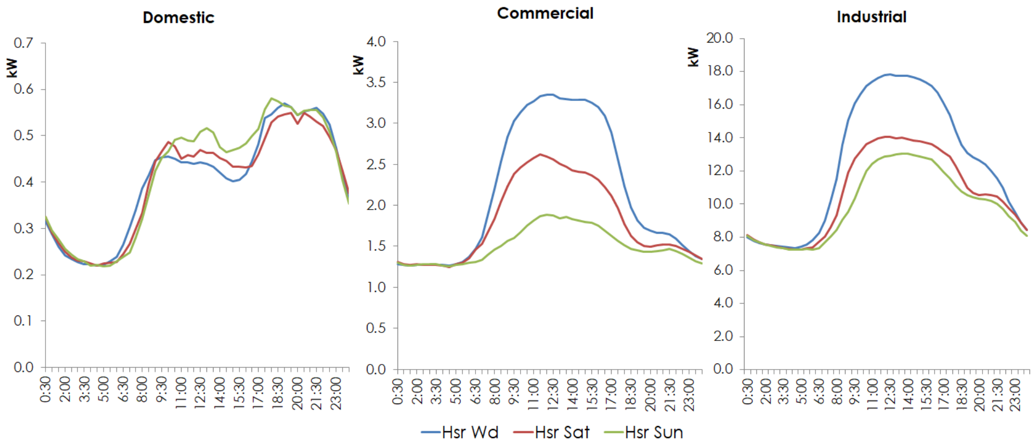
1) The warmest days in the year have no thermal demand component.

2) Any seasonal change in electricity demand profile corresponds to thermal electricity demand.

The warmest days correspond to High Summer Weekday (Hsr Wd), High Summer Saturday (Hsr Sat) and High Summer Sunday (Hsr Sun) for the three stationary sectors as shown in Figure A.2 [1].

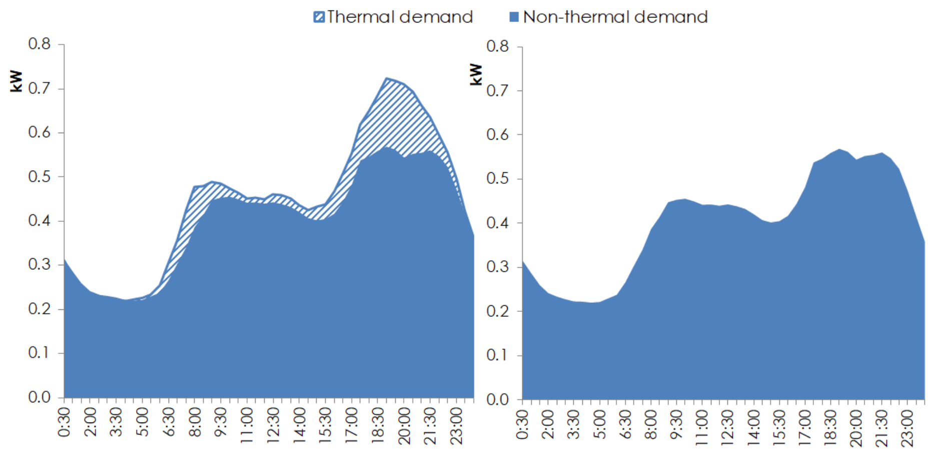
[1] High Summer is defined as between 6th Saturday before 4 Aug and Sunday after 4 Aug

Figure A.2: Electricity demand profiles with the lowest energy demand for the domestic consumer (Elexon, 2017a).



This means that for a domestic consumer non-thermal demand on an Autumn weekday is the same as on High Summer Weekday (Figure A.3). Compiling these profiles according to the type of day allows us to obtain half-hourly non-thermal demand profile for the whole year. This procedure is performed for the base year 2015, following which the resolution is reduced to hourly to better align with other data.

Figure A.3: Extraction of non-thermal demand profile for domestic consumer from the total demand for an Autumn Weekday.



A.1.1.2 Thermal consumer demand profiles

For domestic consumers it was possible to obtain a dataset of natural gas consumption by a gas boiler, $q^{dom}_{CHM,gas}(t,d)$, with hourly resolution and monthly variations from the Cambridge Housing Model (CHM)(BEIS, 2015). This demand data is converted into heat demand $q^{dom}_{CHM,heat}(t,d)$ by applying an average gas boiler efficiency η_{boiler} assumed at a conservative value of 75% (BEIS, 2017d),i.e.

$$q^{dom}_{CHM,heat}(t,d) = q^{dom}_{CHM,gas}(t,d) \cdot 0.75, \quad \forall t \in [1,T], d \in [1,D].$$

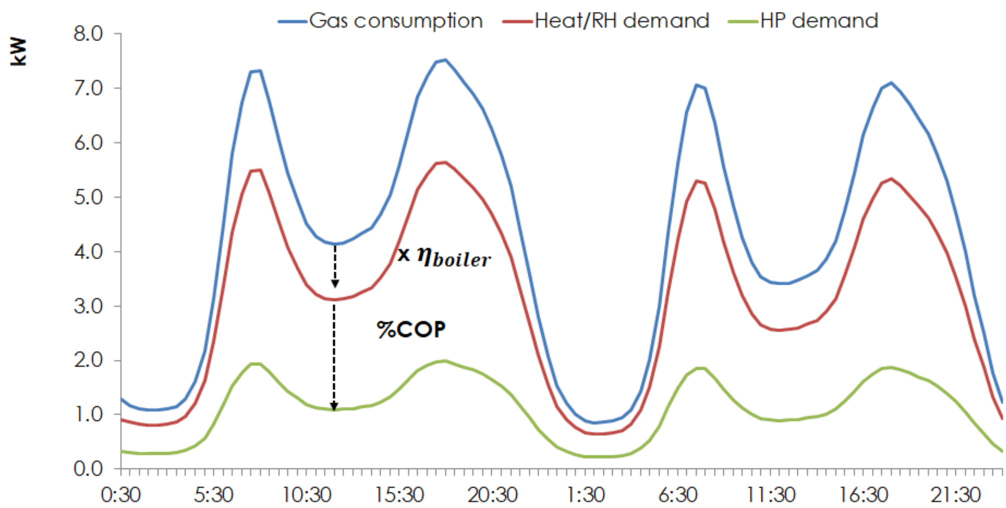
Profile $q^{dom}_{CHM,heat}(t,d)$ is what we take as the electricity demand by a domestic resistance heater (RH) since it has 100% efficiency when converting power demand into heat, i.e. $q^{dom}_{CHM,heat}(t,d) = q^{dom}_{RH}(t,d), \quad \forall t \in [1,T], d \in [1,D]$..

RH demand profile is converted to that of a heat pump (HP) by dividing it by the coefficient of performance (COP) of the heat pump (see Appendix B.3 for COP calculations), i.e.

$$q^{dom}_{HP}(t,d) = \frac{q^{dom}_{RH}(t,d)}{COP(d)}.$$

Figure A.4 shows an example of how energy consumption by a gas boiler is converted into resistance heating and heat pump electricity demand profiles for a domestic consumer.

Figure A.4: Thermal demand for a domestic gas boiler converted into demand for resistance heater, and a heat pump on the 1-2 January 2010/11 (Cambridge Energy, 2017).



For non-domestic sectors it was not possible to find data for thermal demand,

Figure A.5: Standard electricity demand profiles for commercial consumer, 1 Jan 2015. Source: (Elexon, 2017a).

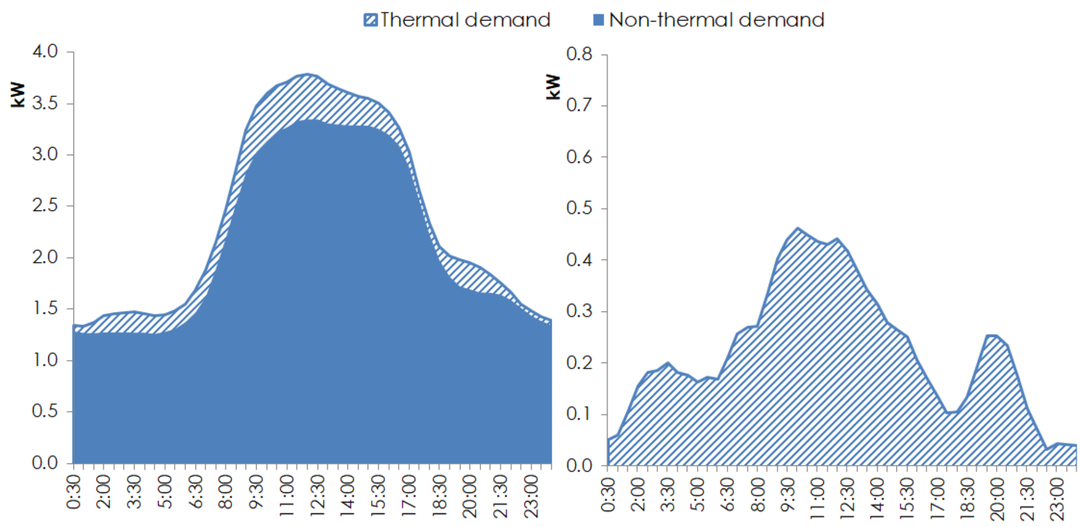
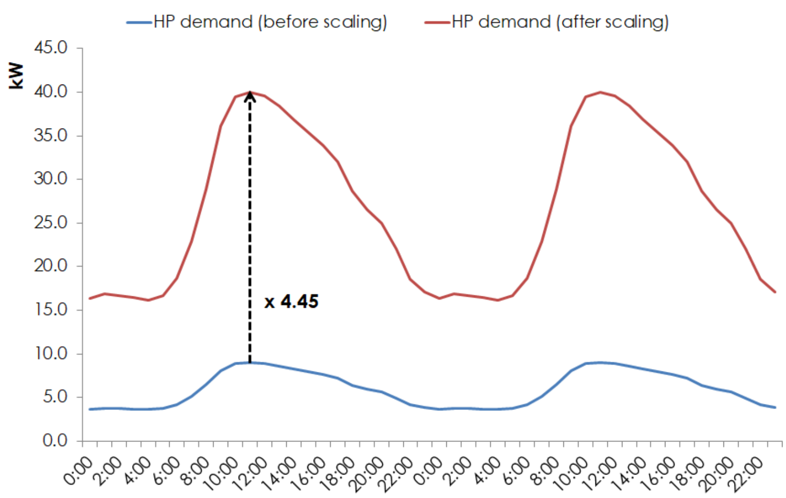


Figure A.6: Example of scaling the HP demand profile for an industrial consumer on the 1-2 December 2015.



hence for commercial and industrial consumers it is assumed that the thermal demand pattern by taking the difference between the total demand and the non-thermal demand profiles obtained in Section A.1.1.1, i.e. $l^{sec}_{tot}(t,d) - l^{sec}(t,d), \quad \forall sec \in \{com, ind\}$ (Figure A.5).

Now the profile shown on the right side of Figure A.5 gives the pattern but not the right magnitude of the electricity demand by a non-domestic heat pump.

This is evident because maximum electricity input capacity for a commercial heat pump averages at around 10kW(Panasonic, 2017), whereas according to the chart it is 1.4kW. Hence, for commercial and industrial sectors thermal demand profiles are scaled in accordance with the power rating capacities for commercially available models. These average at 10kw and 40kW for commercial and industrial sectors respectively (Panasonic, 2017)(The Renewable Energy Hub UK, 2017).

Figure A.6 demonstrates the scaling procedure for thermal demand of an industrial consumer on the 1st and 2nd of December when thermal demand peaks. It can be seen that the peak is increased from 9kW to 40kW. A similar procedure is performed for the commercial sector where individual thermal demand peak is increased from 1.4 to 10kW as per previous discussion.

A.1.2 Transportation sector

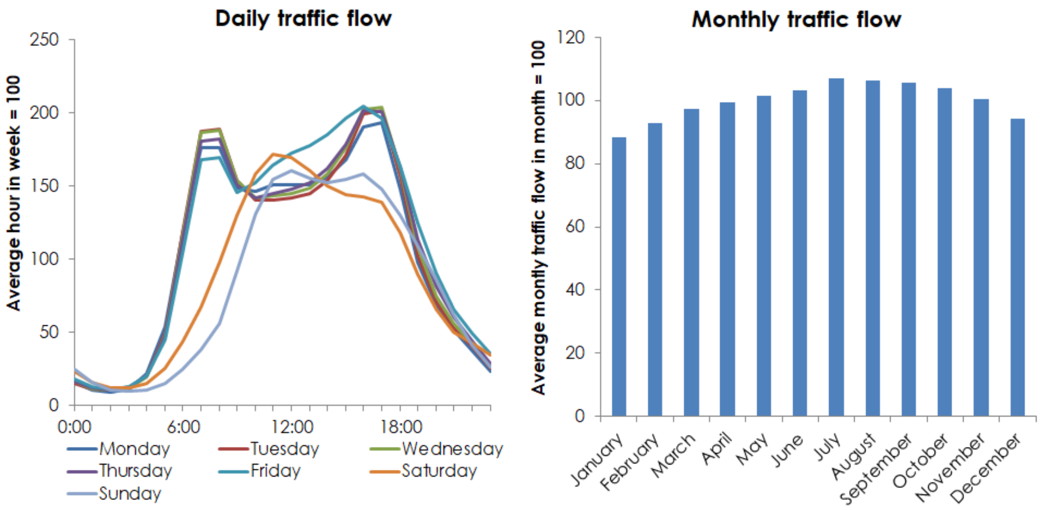
The electric transportation sector is modelled as consumer agents of type 8, i.e. in possession of an electric store. From the perspective of the grid, the transport agent represents a purely flexible load due to charging, i.e. $l^{EV,ch}(t,d)$. From the perspective of the electric vehicles (EVs), transport consumers also have a non-deferrable profile, which corresponds to the vehicles discharging during moving, $l^{EV,dc}(t,d)$. Together, energy capacity (E^{EV}), power capacity ($l^{EV,max}$), and the discharge profile ($l^{EV,dc}(t,d)$) define the operational constraints of the transport agent. In this section we show how these are obtained.

Since the number of EVs in the UK is still very low we use the traffic flow data for conventional vehicles and assume it is the same as for EVs. Figure A.7 shows the daily and monthly traffic flow distribution, $f_1(t,d)$ and $f_2(m)$. We calculate the annual traffic flow distribution $f(t,d,m)$ for each hour t, day d and month m in a reference year by multiplying and normalising the two distribution together, i.e.

$$f(t,d,m) = \frac{f_1(t,d) \cdot f_2(m)}{100}.$$

The resulting distribution offers data on the flow of traffic relative to the average day in the year. We convert this distribution into an annual energy consumption

Figure A.7: Traffic distribution by time of day on all roads in Great Britain, 2015



Source: Vehicle Licensing Statistics (DfT, 2016)

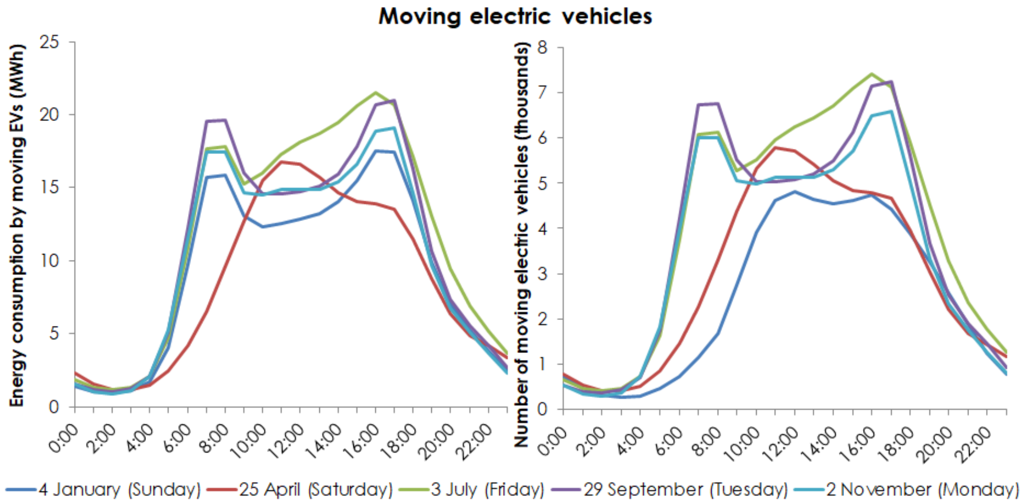
profile by multiplying it by the average hourly energy consumption value, which for 2015 comes to 9.9 MWh for the whole fleet of electric vehicles (taking into account 80% throughput efficiency), i.e. $108,000 MWh \cdot 0.8/8760$ (National Grid, 2017a). The resulting demand profile corresponds to the discharge profile of a fleet of electric vehicles (Figure A.8, left).

Considering that an average driver covers 10,701 km in 368h per year (Department for Transport (DfT), 2016) and a 0.1 kWh/km average efficiency of an EV(Energuide, 2017), the average energy consumption by a single vehicle is calculated at 2.9kWh per hour. By dividing the discharge profile of a total fleet by 2.9kWh it is possible to calculate how many electric vehicles are on the move (Figure A.8, right). Our calculations show that on average vehicles are moving 5% of the time meaning that the rest of the time they are stationary.

Next, we calculate the number of stationary vehicles ($N^{EV}_{stat}(t,d)$) by subtracting the number of moving vehicles $N^{EV}_{move}(t,d)$ from the total number of EVs in the system in 2015 $N^{EV}_{tot} = 51,085$ according to (National Grid, 2017a), i.e.

$$N^{EV}_{stat}(t,d) = N^{EV}_{tot}(t,d) - N^{EV}_{move}(t,d), \quad \forall t \in [1,T], d \in [1,D].$$

Figure A.8: Modelled energy consumption and numbers of moving electric vehicles, 2015.



Assumptions regarding EV operation.

1. If an electric vehicle is stationery it is charging;
2. State of charge of the battery at the beginning of the day is the same as at the end of the day.

Using the above assumption information, we calculate the charging profile of the EV fleet, $l^{fleet,ch}(t,d), l^{fleet,dc}(t,d)$ by distributing the daily energy demanded by the moving fleet of EVs proportionally to the number of vehicles that are stationary (Figure A.9). We calculate individual transport consumer agent charging and discharging profiles (each representing 1000 EVs) by dividing $l^{fleet,ch}(t,d), l^{fleet,dc}(t,d)$ by the number of EVs assumed in the system, i.e. $N^{EV} = 51 thousand$ in 2015 according to (National Grid, 2017a). Finally, we calculate the energy and charging capacities by taking the maximum of the cumulative energy and charging profiles over the whole year. Figure A.10 (left) demonstrates how the level of energy stored by a fleet of 1000 vehicles changes over the day. It is possible to see that the maximum state of charge is reached at around 06:00 when most vehicles are stationary. As EV fleet continues to move throughout the day, the battery discharges reaching the minimum at around 21:00. The maximum value of the energy level in the fleet battery determines the storage capacity of the transport consumer, $E^{max,trans}$.

The right chart in Figure A.10 shows how much charging occurs in each hour for a fleet of 1000 vehicles (representing 1 transport consumer). The most energy is charged during the period 15:00-18:00 when electric vehicles become stationary. The maximum value determines the power at which the transport consumer is able to draw power from the grid, $l^{max,trans}$.

Figure A.9: Modelled energy consumption and numbers of stationary electric vehicles, 2015.

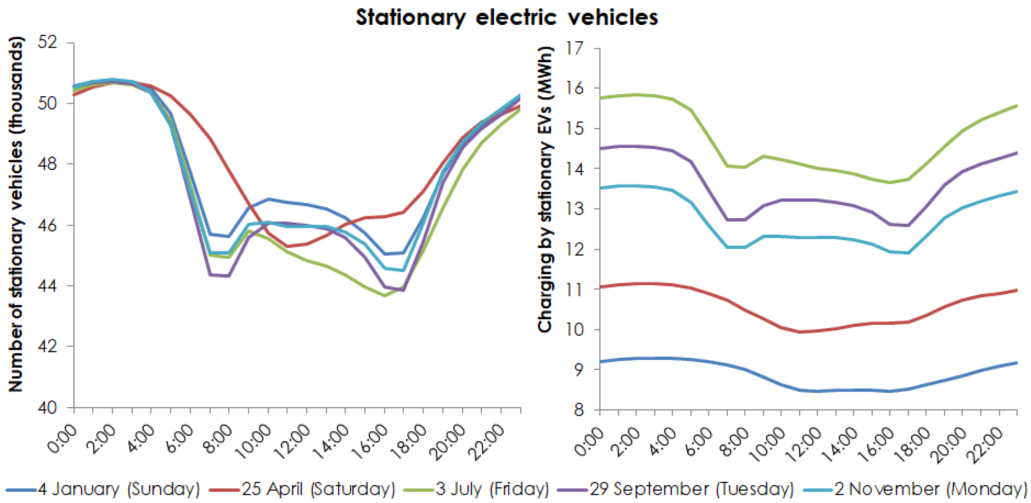
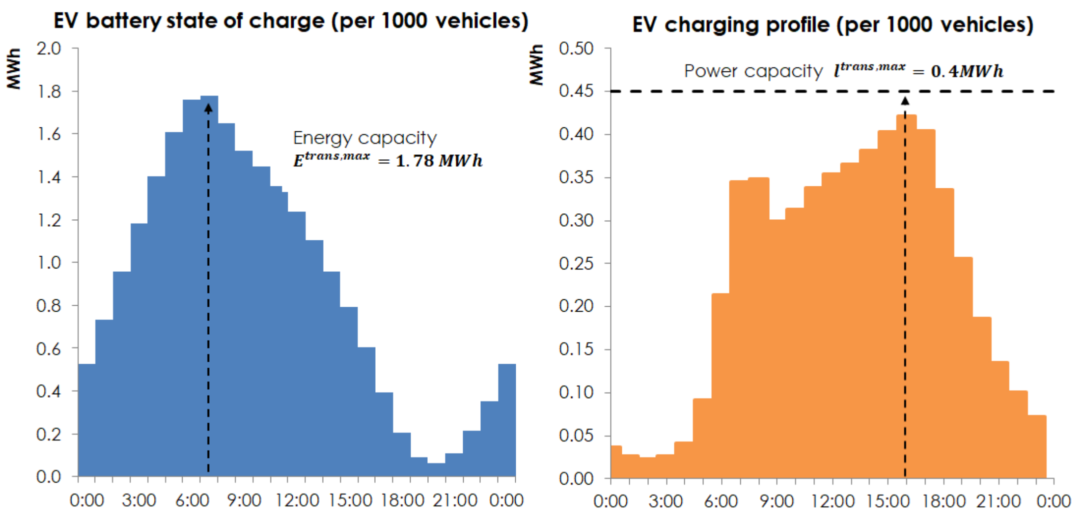


Figure A.10: Cumulative energy and charging profiles for 1000 electric vehicles, Friday, 10 July 2015. Source: own modelling.



The storage capacity of a transport consumer ($E^{EV,max}$) corresponds to the battery capacity of a thousand electric vehicles available for shifting rather than the maximum battery capacity. This is equivalent to approximately 9% of the total available EV battery storage capacity (based on the average 20kWh battery size) suggesting that without vehicle-to-grid services a minor portion of energy demanded by electric vehicles is available for shifting. This is because consumers do not discharge more than 40% of the vehicles as well as moving throughout the day. The power capacity ($l^{EV,max}$) corresponds to the average charging power capability of the fleet throughout the day. Hence, a thousand electric vehicles operating in a default manner are equivalent to a 1.78MWh electrical storage with a power capacity of 0.45MW.

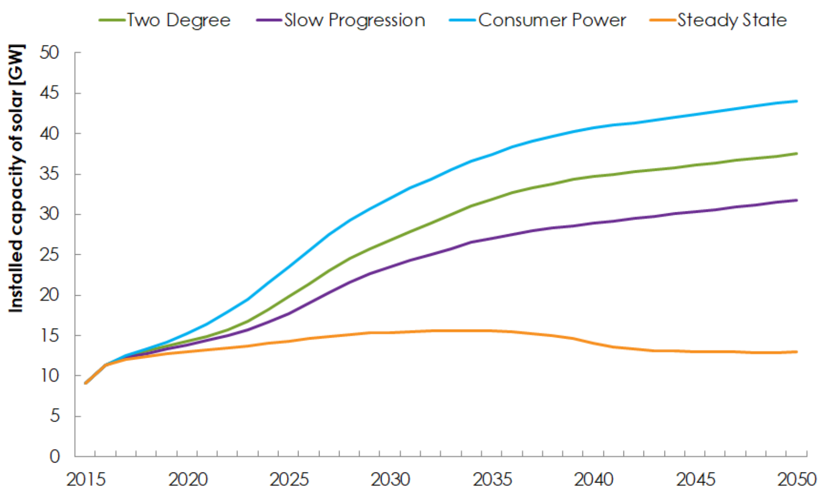
Appendix B

Modelling consumer technologies

B.1 Solar PV

Although the National Grid provides data on the total solar capacity up to 2050 at distribution and transmission levels, it does not state how much of it might belong to end-users and how much to the system (Figure B.1). Hence, the challenge in modelling solar generation was in splitting the total capacity between different end-user sectors and the system.

Figure B.1: Projected installed solar capacity in Great Britain at transmission level. Source: (National Grid, 2017a).



In order to allocate total solar capacity the each individual sector, we turn to the dataset offered by the Department for Business, Energy & Industrial Strategy, which specifies which solar installations under Feed-In-Tariff scheme (FiT) belong to each of the three economic sectors (BEIS, 2017b). Table B.1 summarises the data for total capacities and number of installations within each sector for the period 2015-2017. Whereas, the dataset is exhaustive in terms of domestic installations, it does not include all commercial and industrial solar capacity. Other installations, such as those under the renewable obligation scheme, do not specify which sector they belong to. Hence, two assumptions are made in order to allocate total solar capacity.

Table B.1: Solar deployment under FiTs in each economic sector, 2015-2017 (BEIS, 2017b)

	2015	**2016**	**2017**
Domestic			
Capacity (MW)	2069	2558	2676
Number of installations	603,421	746,199	780,484
Commercial			
Capacity (MW)	723	1059	1459
Number of installations	16,834	24,664	33,988
Industrial			
Capacity (MW)	87	148	252
Number of installations	1088	1847	3159

Assumptions regarding solar PV installations.

1. All domestic installations are deployed under the FiT scheme.

2. The ratio of non-thermal demand peak to solar generation capacity per consumer is the same across all sectors.

3. The share of total solar capacity allocated to each consumer sector and the system remains constant across the whole simulation period 2015-2050.

4. 50% of solar capacity belongs to end-users and 50% to the system (DECC, 2014).

5. Non-domestic solar capacity is equally split between commercial and industrial sectors.

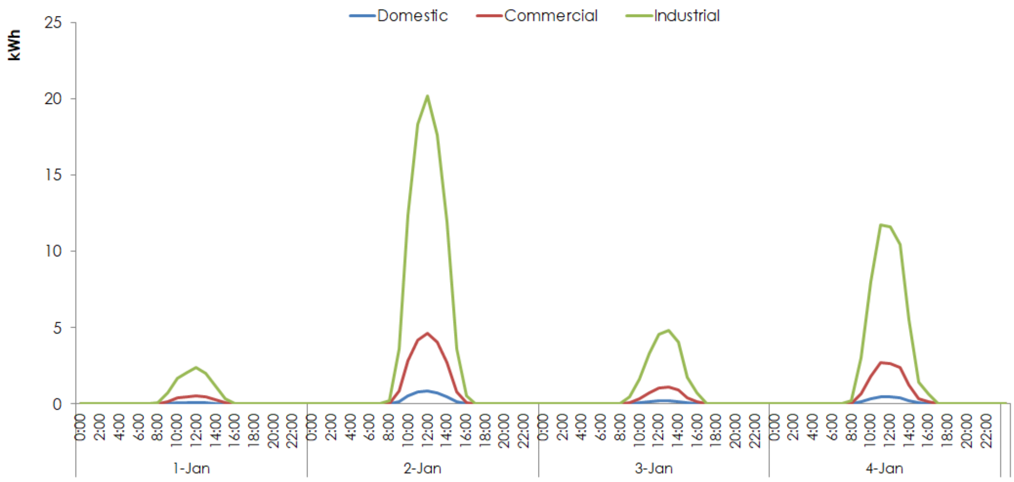
Based on assumption 1, and information in Table B.1 it is possible to say that 25% of total installed solar capacity belongs to domestic sector which sees an average installation of 3.5kW. Hence for domestic consumer the non-thermal peak to solar capacity amounts to 0.166. Utilising assumption 2, we calculate the average installation size for commercial and industrial consumers at 18kW and 80kW (based on non-thermal demand peaks of 3.1kW and 13.7kW). Finally, by using assumptions 4 and 5 and by knowing the average size for non-domestic installations, we calculate the number of installations for commercial and industrial sectors. Table B.2 summarises this information.

Table B.2: Number of solar installations and average size of installation per individual consumer assumed for 2015-2017.

Type of installation	**2015**	**2016**	**2017**
Domestic			
Share of total capacity	25%	25%	25%
Average installation size (kW)	3.5	3.5	3.5
Number of installations	603,421	746,199	780,484
Commercial			
Share of total capacity	12.5%	12.5%	12.5%
Average installation size (kW)	18.5	18.5	18.5
Number of installations	55,386	76,942	83,362
Industrial			
Share of total capacity	12.5%	12.5%	12.5%
Average installation size (kW)	80.8	80.8	80.8
Number of installations	12,695	17,636	19,107
System level			
Share of total capacity	50%	50%	50%
Installation capacity (MW)	363,296	431,452	898,979
Total installed capacity (MW)	**726,591**	**862,903**	**898,979**

We then use historical solar generation profile taken from (National Grid, 2015b) and the information compiled in Table B.2 in order to calculate individual solar generation profiles per individual consumers across the three economic sectors (Figure B.2). To model future adoption of solar, we scale individual generation profiles by the projected capacity increase as demonstrated in Figure B.1(see Appendix C.2). The reader is reminded that each modelled consumer agent represents 1,000 real life end-users, and so in the modelling framework the standard generation profiles shown in Figure B.2 are multiplied by 1000 to represent the solar generation profile for each consumer agent.

Figure B.2: Standard solar generation profiles for individual end-users in different sector, 1-4 Jan, 2014. Source: (National Grid, 2015b).



B.2 Electrical storage (ES)

Electrical storage is recognised as a promising solution to balancing renewable energy in the system. Rapid development of electric vehicles is resulting in lowering costs for lithium based batteries making them accessible not only to large consumers within industrial and commercial sectors but also to residential and smaller commercial end-users. In fact, the National Grid projects non-transmission level storage capacity to reach 2.4 GW in the Steady State scenario and almost 6GW in the Two Degrees scenario by 2040 (National Grid, 2017a). Batteries are often considered together with rooftop solar, such as in the case of TeslaPower wall as a way of balancing renewable energy supply. Hence, the demand for renewables also drives the rate of storage deployment.

There are different types of electrical storage, however in this work we consider a lithium battery similar to a Tesla PowerWall due to its commercial availability. Batteries are characterised by a minimum and maximum energy capacity constraints $E_{ES}^{min,c}$ and $E_{ES}^{max,c}$, minimum and maximum power constraints $l_{ES}^{min,c}$ and $l_{ES}^{max,c}$, and energy efficiency η_{ES}^{c}.

B.2.1 Technical constraints of the ES (Karoline et al., 2016)

Electric storage must obey the following technical constraints:

ESC1. The charge $l^{ch,c}(t,d)$ and discharge $l^{dc,c}(t,d)$ of ES must lie within the power constraints of the battery at all times throughout the day:

$$l_{ES}^{min,c} \leq l_{ES}^{ch,c}(t,d) \cdot b_{ES}(t,d) \leq l_{ES}^{max,sec},$$
$$l_{ES}^{min,c} \leq l_{ES}^{dc,c}(t,d) \cdot (1 - b_{ES}(t,d)) \leq l_{ES}^{max,c},$$

Where $b_{ES}(t,d)$ is a binary variable to prevent simultaneous charge and discharge of the battery.

ESC2. The net amount of energy going into the ES is bound by the store efficiency:

$$E_{ES}^{net,c}(t,d) = \eta_{ES}^{c} \cdot l_{ES}^{ch,c}(t,d) - l_{ES}^{dc,c}(t,d).$$

ESC3. Total available energy in the battery $E_{ES}^{c}(t,d)$ is the sum of the available energy in the previous time period and the net charge going into the ES:

$$E_{ES}^{c}(t,d) = E_{ES}^{c}(t-1,d) + E_{ES}^{net,c}(t,d).$$

ESC4. The amount of discharge $l^{dc,c}(t,d)$ is limited by the available energy in the store:

$$l_{ES}^{dc,c}(t,d) \leq E_{ES}^{c}(t,d).$$

ESC5. Total available energy in the battery $E_{ES}^{c}(t,d)$ must be within the minimum and maximum ES capacity constraints:

$$E_{ES}^{min,c} \leq E_{ES}^{c}(t,d) \leq E_{ES}^{max,c}.$$

ESC6. At the end of the day the amount of charge is the same as at the beginning:

$$E^c_{ES}(0,d) = E^c_{ES}(T,d).$$

The above constraints are true $\forall c \in \mathscr{C}, t \in [1,T], d \in [1,D]$.

Whilst the discharge profile, $l^{c,dc}_{ES}(t,d)$ is a decision parameter for the stationary consumers, it is an input for the transportation sector as calculated in A.1.2 and constitutes a constraint for operating the storage.

B.2.2 Estimating ES parameters

For the residential household the maximum energy capacity per individual consumer is assumed as 10kWh and maximum power as 5kW based on the power specifications of a 13.5kWh Tesla PowerWall battery assuming that some consumers might have smaller batteries (Tesla, 2017). For commercial and industrial end-users the stores are scaled based on the total energy consumption in comparison to the domestic consumer. Hence, if the annual consumption by a domestic household is 22 MWh and 35 MWh by commercial business, the ES capacity is calculated as $\frac{34.6}{21.9} \cdot 10 = 16MWh$. Similarly for an industrial end-user, which has an annual demand of 238kWh, ES capacity results in $\frac{238.5}{21.9} \cdot 10 = 109kWh$ energy capacities. The power constraints are calculated as half the capacity value again based on the domestic ES power-to-capacity ratio which is approximately 1:2.

For the transportation sector, the available capacity per vehicle is calculated as $E^{max,trans}_{ES}$=2.9kWh and the maximum power as half the value, i.e. $l^{max,ind}_{ES}$=1.45kW (calculated considering the whole fleet of EVs in Britain as one vehicle). The efficiency for all electrical stores is assumed to be 0.8 and the minimum energy capacity and power to be 0, i.e. $\eta^{sec}_{ES} = 0.8, E^{min,sec}_{ES} = 0 = l^{min,sec}_{ES} \quad \forall sec \in \{dom, com, ind\}$[1].

B.3 Electric heating (EH)(Dejvises, 2012)

Heating electrification contributes a major part to the UK 2050 decarbonisation goals. In this model two types of electric heating are considered: heat pumps (HP) and resistance heating (RH). Resistance heating contributes around a quarter of an-

[1] This is based on Tesla PowerWall batteries claiming available capacity rather than total battery capacity which includes the discharge limitation

nual electricity consumption in the domestic sector today, whilst it is projected that by 2030 around 160 TWh electricity demand will come from 6.8 million heat pumps installed across all economic sectors (CCC, 2013). The mathematical formulation of the two technologies is very similar with the only difference being the coefficient of performance (COP).

A **heat pump** is a reversible heating, ventilation, and air conditioning unit, which transfers thermal energy from a source of heat to a 'heat sink'. Heat pumps operate on the principle of a 'refrigeration-type cycle' (same as air conditioners and fridges) and utilise external power in order to move thermal energy in the opposite direction of spontaneous heat transfer (i.e. from warm to cold) (Bundschuh et al., 2014). In this work we consider **air-source heat pumps** (which draw heat from outside air and upgrade it to a higher temperature to be emitted in the house) due to wider adoption in the UK (CCC, 2013). Heat pumps are characterised by the maximum input electrical power capacity $l^{max,c}$ and efficiency η_{HP}, which determines the coefficient of performance (COP) of the HP.

The COP of the air-to-water heat pump for consumer c, depends on the Carnot efficiency of the HP η_{HP}^{max} taken as 0.4 (Dejvises, 2012) and the relative temperature difference between external air, θ_{ext}, and the heat sink, θ_{TES}, i.e.

$$COP_{HP}^{c}(t,d) = \eta_{HP}^{max} \cdot \frac{\theta_{TES}(t,d)}{(\theta_{TES}(t,d) - \theta_{ext}(t,d))}, \tag{B.1}$$

We take the temperature of the heat sink (the temperature of the heater water) as 323.15K (equivalent to 50°C) and calculate the COP of the heat pump using the average monthly external air temperatures in the UK taken from the Met Office(Met Office, 2017) according to (B.1). Since the temperature fluctuations throughout the year are taken as historical, the COP values also do not change from year to year. In reality of course external air temperatures vary from year to year (especially considering the impact of climate change) and so the value of COP will change. However, this is left as limitation of the model since we do not consider climate change in our simulation.

Similarly, resistance heaters (RH) are characterised by the maximum power constraints ($l_{RH}^{min,c}, l_{RH}^{max,c}$(and efficiency η_{RH}^{c}. However, since all since all of the power used by RH goes into meeting thermal energy demand in (B.1), $COP_{RH} = 1$.

B.3.1 Technical constraints of electric heating resources

EHC1. The power demanded by an electric heater (EH) $l_{EH}^{c}(t,d)$ must be within the minimum and maximum power constraints of the heat pump, $l_{EH}^{min,c} = 0$ and $l_{EH}^{max,c}$:

$$l_{EH}^{min,c} \leq l_{EH}^{c}(t,d) \leq l_{EH}^{max,c}, \quad EH = \{HP, RH\}, \forall t \in [1,T].$$

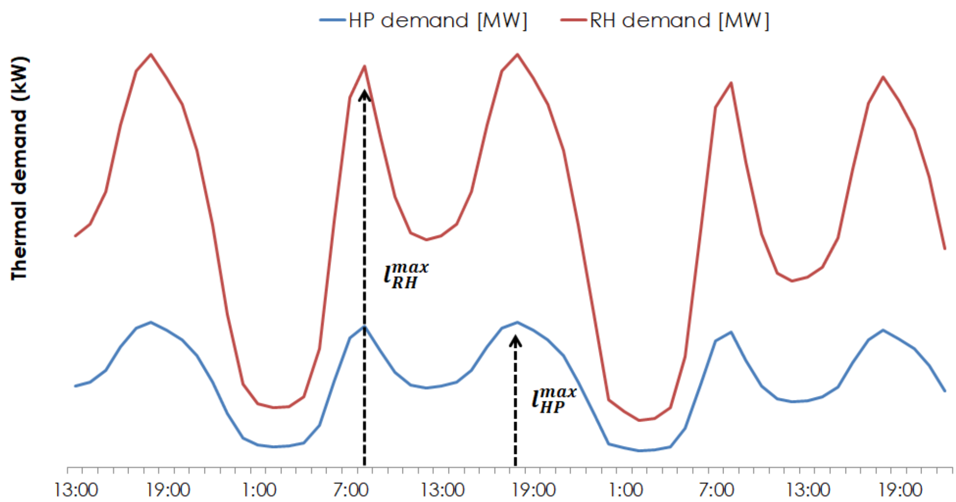
EHC2. The power required by an electric heater $l_{HP}^{c}(t,d)$ to fulfil heat demand $q_{HP}^{c}(t,d)$ is calculated as:

$$l_{HP}^{c}(t,d) = \frac{q_{HP}^{c}(t,d)}{COP_{HP}^{c}(t,d)} \quad \forall c \in \mathscr{C}, t \in [1,T].$$

B.3.2 Estimating parameters of EH

Electric heating is characterised by the maximum input power rating, i.e. $l_{HP}^{sec,max}, l_{RH}^{sec,max}$. In order to obtain these values for individual consumer across domestic and non-domestic sectors, we take the maximum value from the annual consumer thermal demand pattern obtained in Section A.1 (Figure B.3).

Figure B.3: Example of estimation of heat pump and resistance heating capacity for a generic consumer.



B.4 Thermal energy storage

Thermal energy storage (TES) is a mature technology for storing heat and is widely used in the UK. Moreover, thermal storage can help smooth demand peaks resulting from the deployment of electric heating such as heat pumps. For this reason, the dynamics of the HP and RH are considered together with a TES.

A **thermal store** is characterised by minimum and maximum storage capacity $E_{TES}^{min,c}, E_{TES}^{max,c}$, minimum and maximum power flow rate $l_{TES}^{min,c}, l_{TES}^{max,c}$ and efficiency η_{TES}^{c} for each individual consumer c.

Consumers may utilise TES to shift the electricity demanded by the electric heater (HP or RH) by means of charging and discharging the store. Hence, if $q_{EH}^{c}(t,d)$ is the heat generated by an electric heater, $q_{TES}^{ch,c}(t,d), q_{TES}^{dc,c}(t,d)$ are the charge and discharge profiles of TES, the total heat generated by the system is calculated as:

$$q_{EH}^{c}(t,d) - q_{TES}^{ch,c}(t,d) + q_{TES}^{dc,c}(t,d) \tag{B.2}$$

This must be done in agreement with the following technical characteristics of the HP-TES:

B.4.1 Technical constraints of the TES system

TESC1. heat going in and out of the TES must be balanced. Hence, the heat generated directly by an electric heater ($q_{EH}^{c}(t,d)$) and the heat discharged from the TES ($q_{TES}^{dc,c}(t,d)$) must fulfil the charging requirements of TES ($q_{TES}^{ch,c}$) and the non-deferrable heat demand profile by of consumer c ($q^{c}(t,d)$):

$$q_{EH}^{c}(t,d) + q_{TES}^{dc,c}(t,d) = q^{c}(t,d) + q_{TES}^{ch,c}, \quad EH = HP, RH, \forall t \in [1,T].$$

TESC2. The net amount of energy going into the TES is the difference between thermal charge $q_{TES}^{ch,c}$ and discharge $q_{TES}^{dc,c}$ [2]:

$$E_{TES}^{net,c}(t,d) = q_{TES}^{ch,c}(t,d) - q_{TES}^{dc,c}(t,d).$$

TESC3. TES charge $q_{TES}^{ch,c}(t,d)$ and discharge $q_{TES}^{ch,c}(t,d)$ are bound by the TES energy

[2] Here the heat loss in the pipes is ignored.

flow constraints:

$$q_{TES}^{min,c} \leq q_{TES}^{ch,c}(t,d) \cdot b_{TES}(t,d) \leq q_{TES}^{max,c},$$
$$q_{TES}^{min,c} \leq q_{TES}^{dc,c}(t,d) \cdot (1 - b_{TES}(t,d)) \leq q_{TES}^{max,c},$$

where $b_{TES}(t,d)$ is a binary variable to prevent the storage charging and discharging at the same time.

TESC4. Total available energy in the TES is the sum of the available energy in the previous time period $E_{TES}^{c}(t-1,d)$ adjusted by the store efficiency η_{TES}^{c} plus the net charge going into the store:

$$E_{TES}^{c}(t,d) = \eta_{TES}^{c} \cdot E_{TES}^{c}(t-1,d) + E_{TES}^{net,c}(t,d).$$

TESC5. Total available energy in the TES($E_{TES}^{c}(t,d)$) must be within the TES capacity constraints:

$$E_{TES}^{min,c} \leq E_{TES}^{c}(t,d) \leq E_{TES}^{max,c}.$$

TESC6. At the end of the day the amount of thermal energy in the TES must be the same as at the beginning:

$$E_{TES}^{c}(0,d) = E_{TES}^{c}(T,d).$$

The above constraints are true $\forall c \in \mathscr{C}, t \in [1,T], d \in [1,D]$.

B.4.2 Estimating technical parameters of thermal energy storage

Based on the rate at which thermal power can be extracted from a domestic hot water tank in (Dejvises, 2012), we assume that the thermal output capacity $l_{TES}^{max,sec}$ for a TES is approximately half of its total energy capacity $E_{TES}^{max,sec}$, i.e. $l_{TES}^{max} = 0.5 \cdot E_{TES}^{max,sec}$.

It is assumed that the efficiency of TES $\eta_{TES} = 0.98$ (which corresponds to the heat loss during operation) and the minimum energy stored and power at zero for all sectors, i.e. $E_{TES}^{min,sec} = 0kWh, l_{HP}^{min,sec} = 0 \quad sec = \{dom, com, ind\}$.

Figure B.4 summarises the information on the technical specifications of consumer technologies.

Figure B.4: Technical parameters assumed for consumer technologies.

Technical specifications			Consumer sector			
Technology	**Parameter name**	**Symbol**	**Domestic**	**Commercial**	**Industrial**	**Transport**
ES	Max energy capacity [kWh]	$E_{ES}^{max,c}$	10.0	47.0	226.0	1.8
	Min energy capacity [kWh]	$E_{ES}^{min,c}$	0.0	0.0	0.0	0.0
	Max power capacity [kW]	$l_{ES}^{max,c}$	5.0	23.5	113.0	0.5
	Min power capacity [kW]	$l_{ES}^{min,c}$	0.0	0.0	0.0	0.0
	Throughput efficiency	η_{ES}^{c}	0.8	0.8	0.8	0.8
TES	Max energy capacity [kWh]	$E_{TES}^{max,c}$	4.7	22.0	106.2	-
	Min energy capacity [kWh]	$E_{TES}^{min,c}$	0.0	0.0	0.0	0.0
	Max power capacity [kW]	$l_{TES}^{max,c}$	2.4	11.0	53.1	-
	Min power capacity [kW]	$l_{TES}^{min,c}$	0.0	0.0	0.0	-
	Throughput efficiency	η_{TES}^{c}	0.98	0.98	0.98	0.98
HP	Max power capacity [kW]	$l_{HP}^{max,c}$	2.1	10.0	40.0	-
	Min power capacity [kW]	$l_{HP}^{min,c}$	0.0	0.0	0.0	0.0
RH	Max power capacity [kW]	$l_{RH}^{max,c}$	5.6	30.2	121.0	-
	Min power capacity [kW]	$l_{RH}^{min,c}$	0.0	0.0	0.0	-

Appendix C

Future Energy Scenarios (FES)

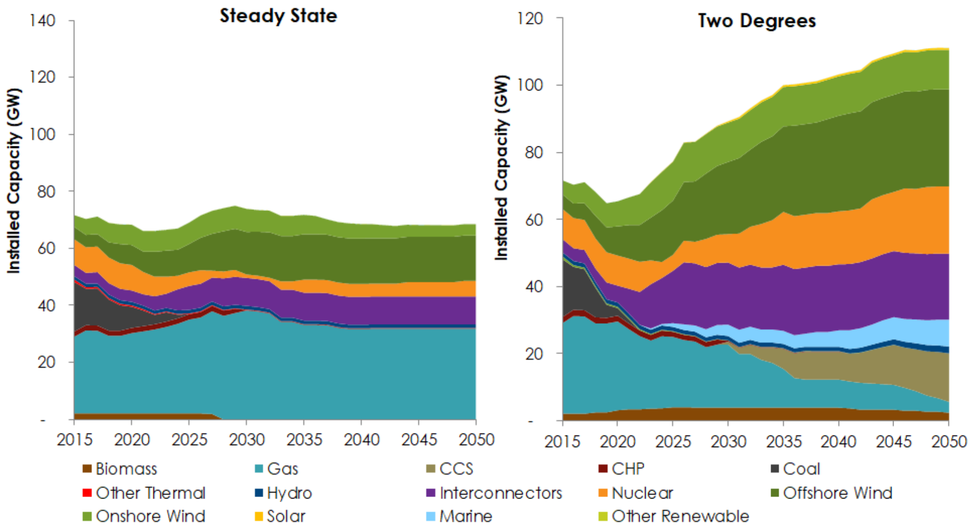
We consult the future energy scenarios (FES) provided by the (National Grid, 2017a) in order to model the future evolution of the British electricity system. The National Grid dataset provides most but not all of the data required, and this chapter described how datasets were selected. As discussed in chapter 4, we focus on the two main cases of national grid evolution: Steady State (the least flexible system with a low penetration of renewables) and Two Degrees+ (the most flexible system with a high penetration of renewables).

C.1 Transmission level resources

For the transmission level generation capacities (including pumped storage) we select the Steady State and Two Degrees scenarios to represent the most pessimistic and the most optimistic cases as shown in Figures C.1 and C.2. Since FES offers only the power capacities for pumped storage, we model energy capacity by scaling the current energy capacity value of 27.6GWh (Taylor et al., 2012) in-line with the future projections for pumped storage installations as predicted by the National Grid.

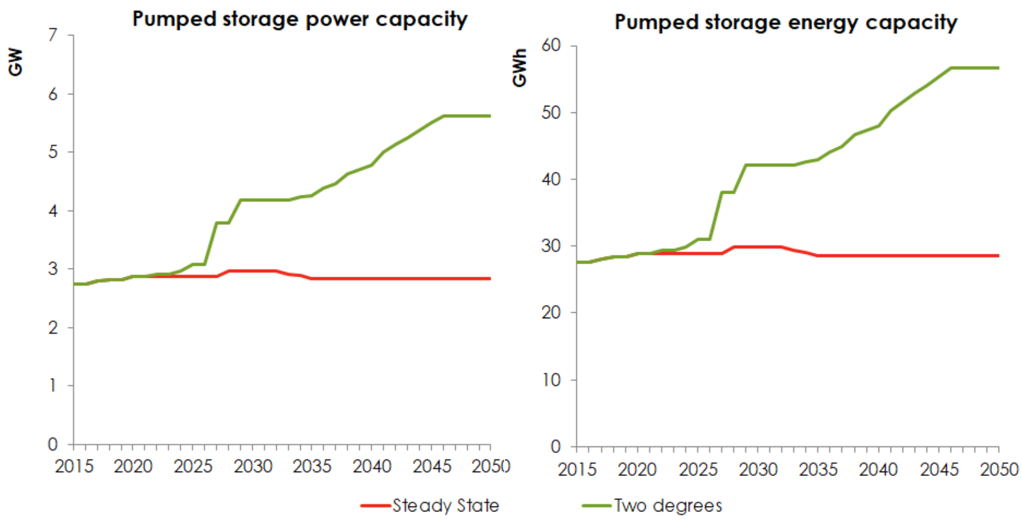
In terms of the price for primary fuels used by the generators, the FES dataset offers information on natural gas, coal and oil (National Grid, 2017a), but not for nuclear and biomass fuels for which reason we consult the data provided by the Department for Business, Energy and Industrial Strategy (DECC, 2012; BEIS, 2016). However, the fuel prices are reported per unit of generated electricity (£/MWhe)

Figure C.1: Projected installed generation capacity in Great Britain at transmission level under Steady State and Two Degrees scenarios. Source: (National Grid, 2017a).



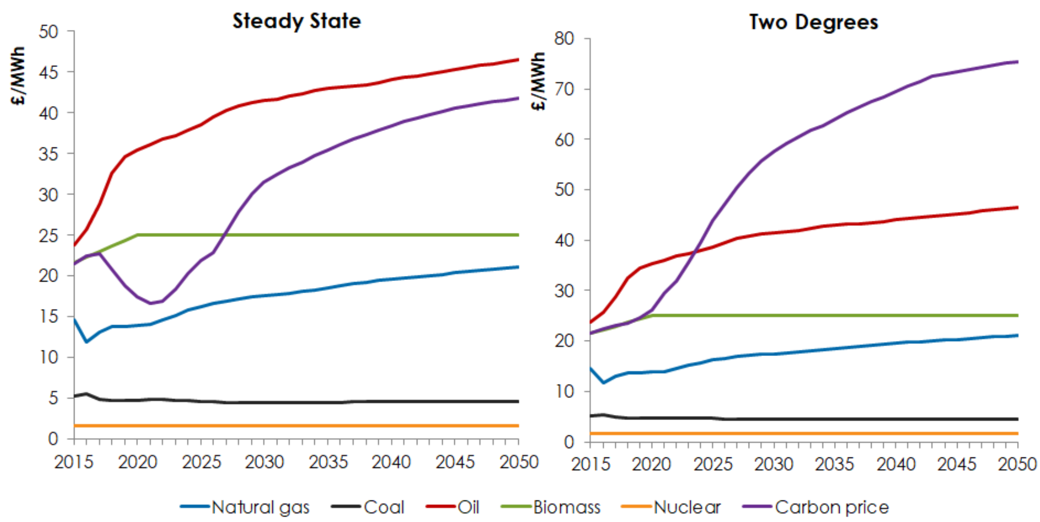
Note: Capacities of renewable resources are adjusted by their load factor.

Figure C.2: Projected installed pumped storage capacity in Great Britain at transmission level under Steady State and Two Degrees scenarios. Source: (National Grid, 2017a).



rather than primary fuel (£/MWhf). We assume a 32% nuclear power plant efficiency in order to convert £5/MWhe to £1.6/MWhf of raw nuclear fuel, and a 36% efficiency in order to convert £60/MWhe to £21.6/MWhf for raw biomass for the base year of 2015 (BEIS, 2016). The report from BEIS suggests an increase in the price of biomass fuel to 72 £/MWhe, which is equivalent to 25.1 £/MWhf. We introduce this increase between 2015 and 2020 and keep the price constant past 2020. On the whole it is difficult to estimate the future price for raw biomass, since the price largely depends on its source and the international markets. Whereas bioenergy (sewage, paper, wood waste etc.) might be free, bio crops (forest, crops, etc.) have a price which is likely to rise, as obtaining this fuel is in direct competition for land with agriculture. Carbon prices, imports and losses are assumed to evolve in-line with the FES scenarios. Figures C.3 and C.4 summarise the information regarding the future evolution of primary fuel and carbon prices.

Figure C.3: Projected prices for primary fuels used in electricity generation under Steady State and Two Degrees scenarios. Source: (National Grid, 2017a).



C.2 Consumer resources

The following section covers the scenarios for the future evolution of consumer technologies.

C.2.1 Electrical storage

A note on assumptions regarding consumer storage. Whilst the National Grid offers data on the future capacity of distribution level storage, it does not say which specific sectors it might be installed and so we make an assumption that capacity is equally split between domestic, commercial, and industrial consumers. However we acknowledge that due to economies of scale larger consumers are likely to take

Figure C.4: Projected system losses and imports under Steady State and Two Degrees scenarios. Source: (National Grid, 2017a).

a higher fraction of the total storage capacity and we explore this issue as part of the sensitivity analysis performed as part of our results.

Figure C.5 demonstrates the most pessimistic (lowest flexibility) and the most optimistic (highest flexibility) cases for the evolution of consumer electric storage capacity, which correspond to the Steady State and Consumer Power storage evolution scenarios provided by (National Grid, 2017a).

To work out the number of stores per sector, we divide the total capacity per sector by an individual storage capacity as calculated in Appendix B.2. From Figure C.6 it can be seen that the number of stores is significantly larger under the Consumer Power scenario compared to Steady State contributing to a higher level of consumer flexibility.

C.2.2 Solar PV

For consumer solar, National Grid provides capacities for all installations at the distribution level under Steady Sate and Consumer Power scenarios (Figure C.7). We model future solar capacity within each sector by multiplying the current number of solar PV installations calculated in Appendix B.1 by the capacity scaling factor calculated relative to the base year 2015 (Figure C.7). From Figure C.8 we can see

Figure C.5: Projected capacity of electrical storage installed at the distribution level across different sectors in Great Britain under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a).

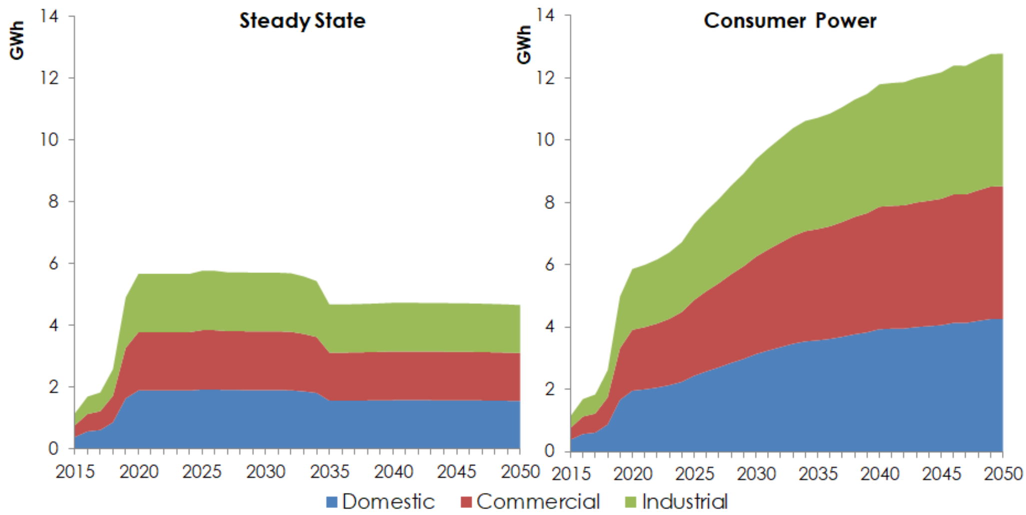
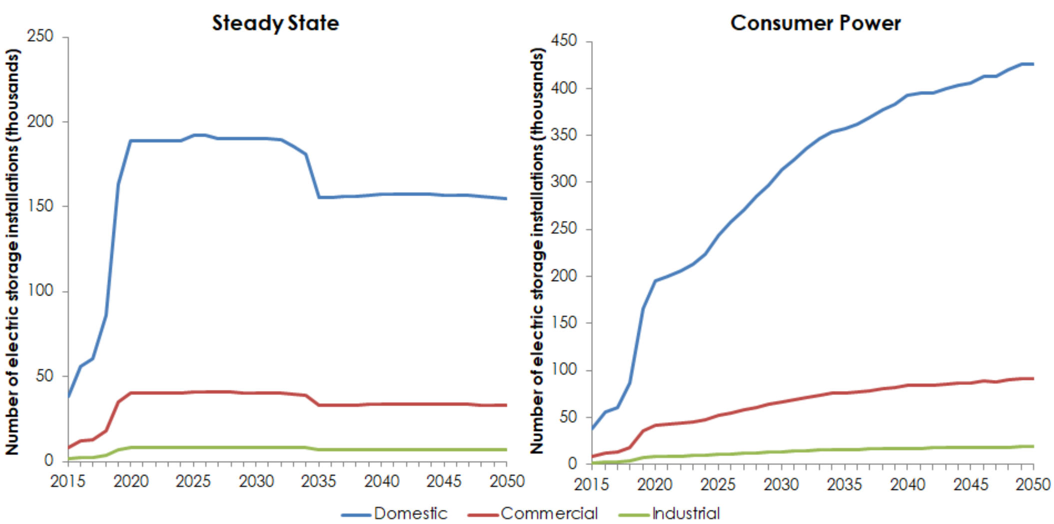


Figure C.6: Projected number of electrical storage installed at the distribution level across different sectors in Great Britain under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a).



that even though the capacity of solar PV has been assumed to be the same across the three consumer sectors, the number of domestic installations is much larger due to a lower individual capacity.

Figure C.7: Projected installed solar capacity in Great Britain at distribution level under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a).

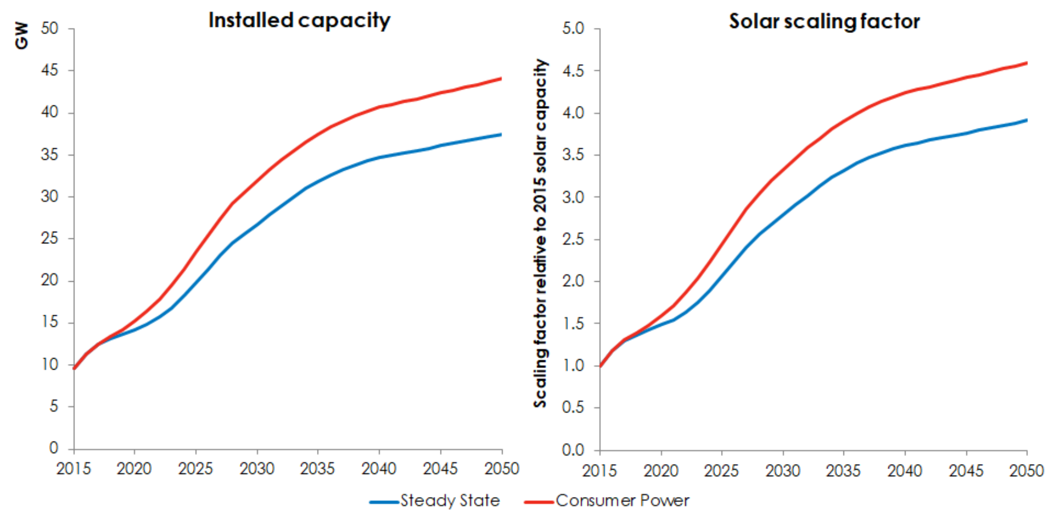
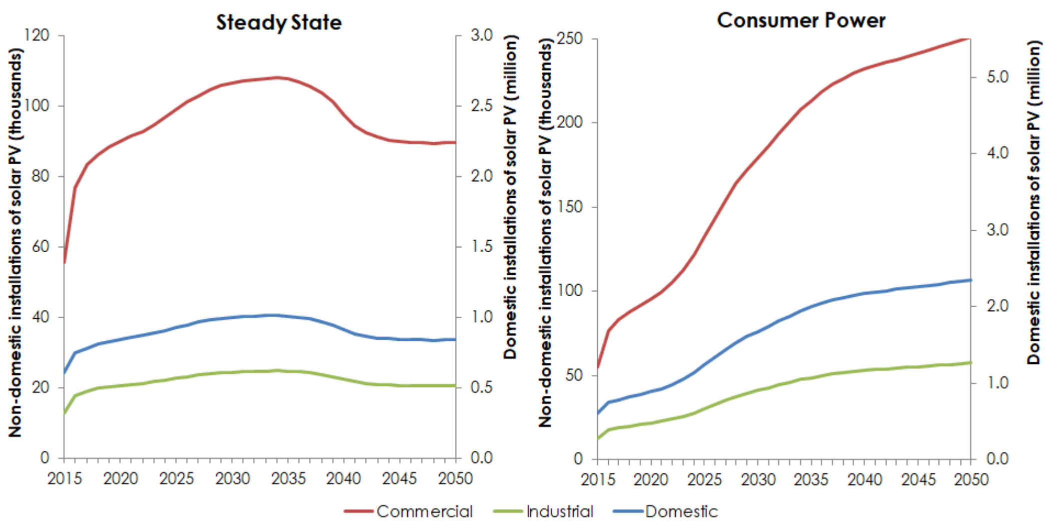


Figure C.8: Projected number of solar PB installations in Great Britain at distribution level under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a).

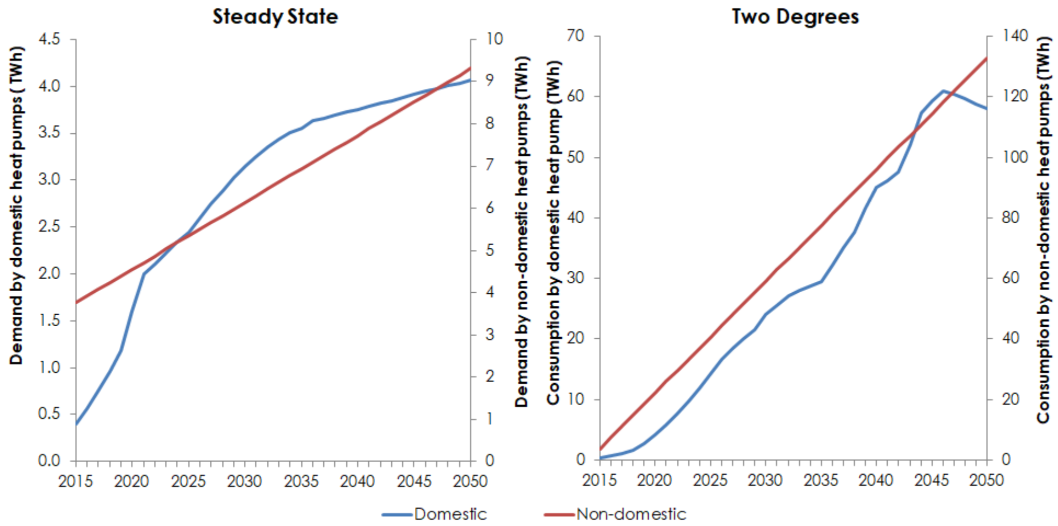


C.2.3 Electric heating

We calculate the number of heat pumps in the system by dividing the annual energy consumed by HPs aggregator across each sector by the annual energy demand of a single HP calculated in Section B.3 (Figure C.9). Whilst the FES provides data for the domestic sector, for non-domestic consumers we consult the report on future HP adoption provided by the Committee on Climate Change (CCC, 2013).

The report provides the predicted values for annual electricity consumption by non-domestic heat pumps under Default and Critical pathways, which is aligned with the Steady State and Two Degrees FES scenarios. We then make an assumption that all non-domestic heat pumps are split equally between commercial and industrial consumers in terms of the total input capacity. Figure C.10 shows the calculated number of installed heat pump within each stationary sector.

Figure C.9: Projected annual consumption by heat pumps in domestic and non-domestic sectors in Great Britain under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a; CCC, 2013).



Similarly to the data on heat pumps, for resistance heaters the FES dataset offers information only for domestic consumers. In order to calculate the annual contribution of resistance heating sources in the non-domestic sectors, we subtract the already calculated annual energy demand by the heat pumps (Figure C.9) from thermal demand of non-domestic consumers (represented by cooling and ventilation, low temperature processes, refrigeration, space and heating) (Figure C.11). In order to obtain the numbers of non-domestic RH installations, we divide the annual energy demand values for each sector by the individual RH consumption values in the reference year 2015. To model the future evolution of non-domestic RHs we apply the growth factors of domestic RHs (Figure C.13).

Figure C.10: Projected heat pumps installations across all sectors in Great Britain under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a; CCC, 2013).

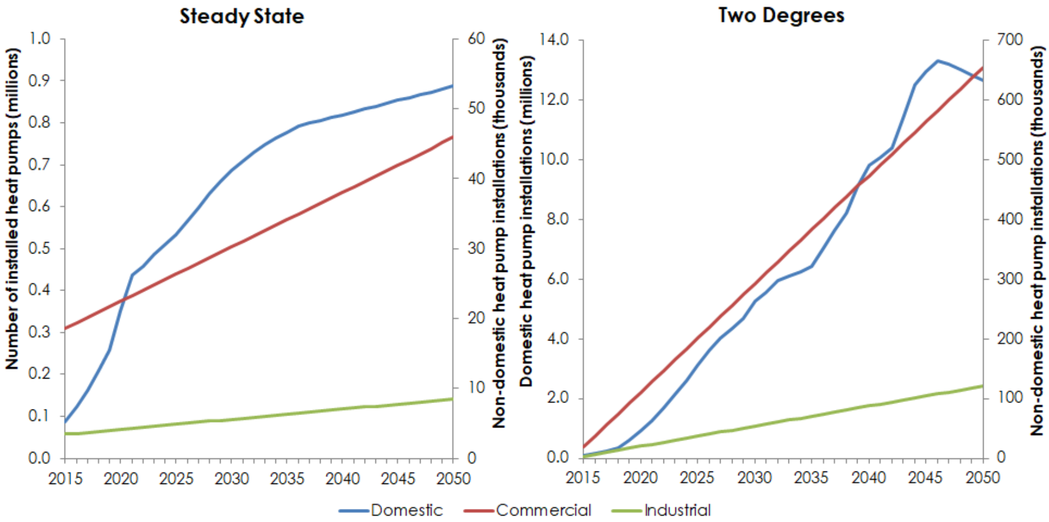
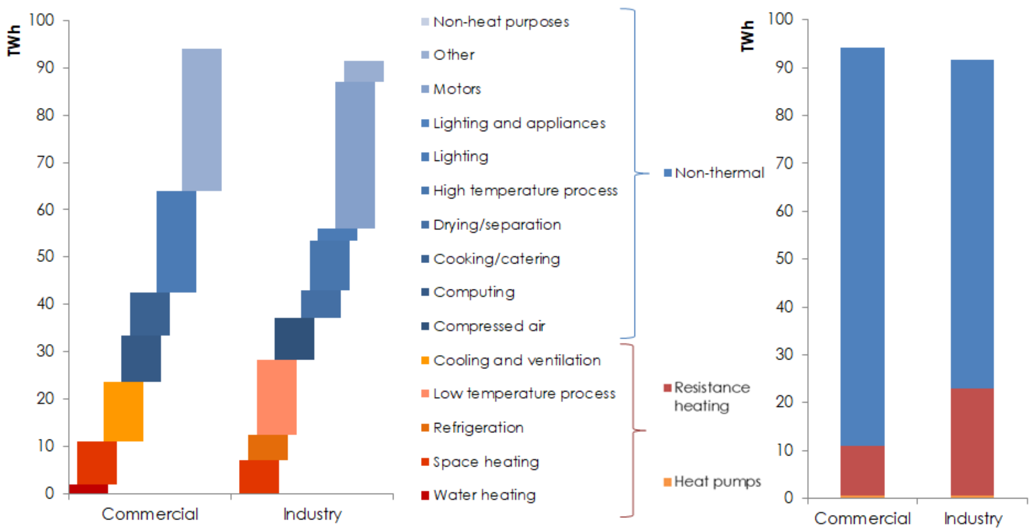


Figure C.11: Projected annual demand by resistance heaters across all sectors in Great Britain under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a; BEIS, 2017c).



Assumptions regarding thermal energy storage (TES). For thermal energy stores it is assumed that for all sectors 50% of consumers with any source of electric heating have a thermal store, which allows us to calculate the number of TESs in the system by dividing the total number of HPs and RHs by two.

Figure C.12: Projected annual demand by resistance heaters across all sectors in Great Britain under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a; BEIS, 2017c).

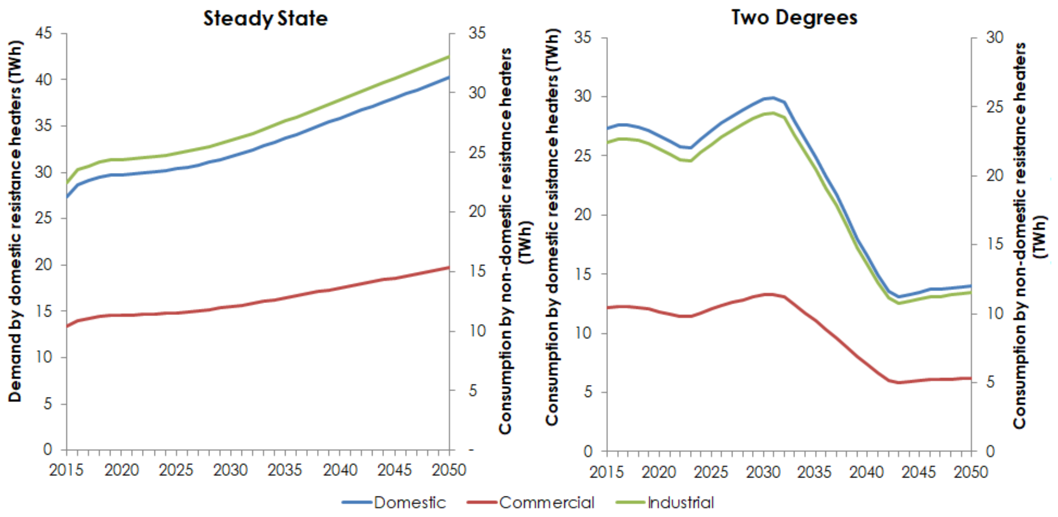
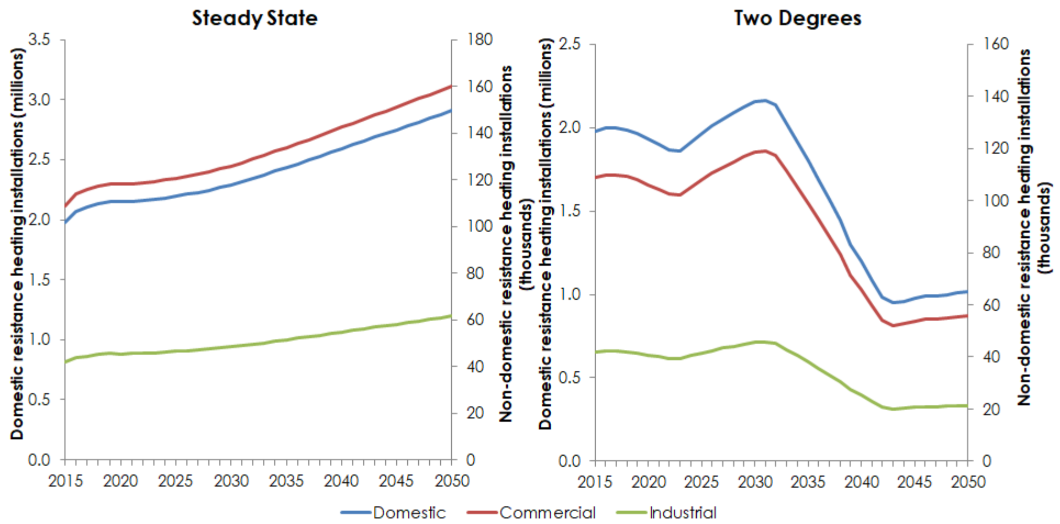


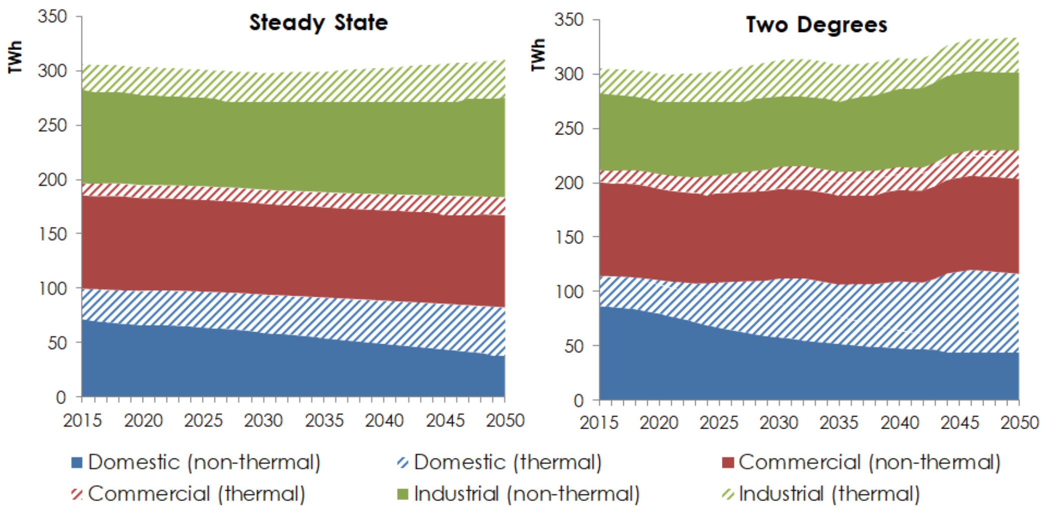
Figure C.13: Projected resistance heating installations across all sectors in Great Britain under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a; BEIS, 2017c).



C.2.4 Non-thermal consumers

We calculate the level of non-thermal consumption by subtracting thermal energy demand (see Appendix C.2.3) from the total energy demand in each sector. We then calculate the number of non-thermal consumers by dividing annual non-thermal consumption by individual non-thermal energy demand for a single non-thermal consumer. Hence, if the commercial sector uses 96.96 TWh/year towards non-thermal resources and an individual commercial consumer uses 16,556 MWh/year, then there are $\frac{96.96}{0.016556} = 5,856$ non-thermal consumers within the commercial sector.

Figure C.14: Projected electricity demand by thermal and non-thermal resources across stationary sectors in Great Britain under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a; BEIS, 2017c).



For the transportation sector the number of non-thermal consumers corresponds to the number of electric vehicles in the system. We use the FES data on Steady State and Two Degrees scenarios as shown in Figure C.16 in order to calculate the total number of electric vehicles in the system represented by plug-in electric vehicles (PEVs) and plug-in hybrid electric vehicles (PHEVs).

Figure C.15: Projected number of non-thermal consumers in different sectors in Great Britain under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a; BEIS, 2017c).

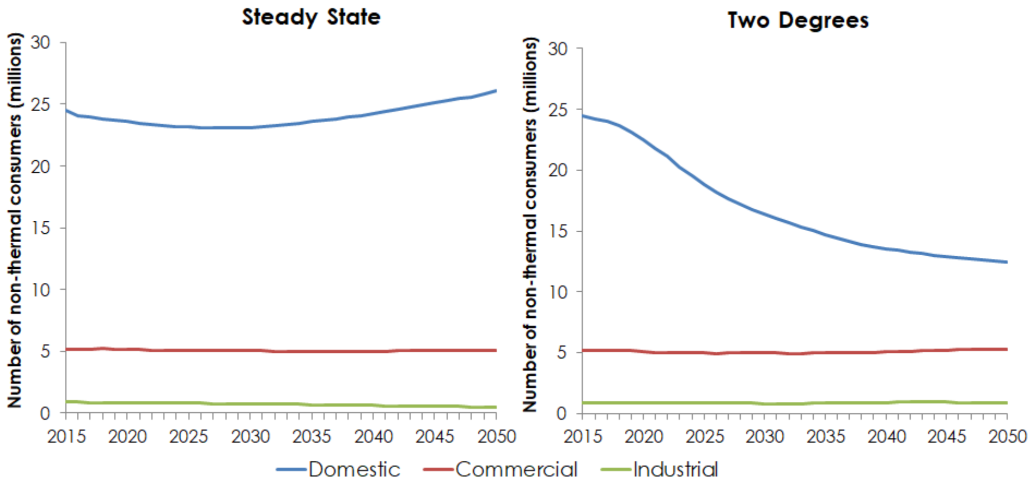
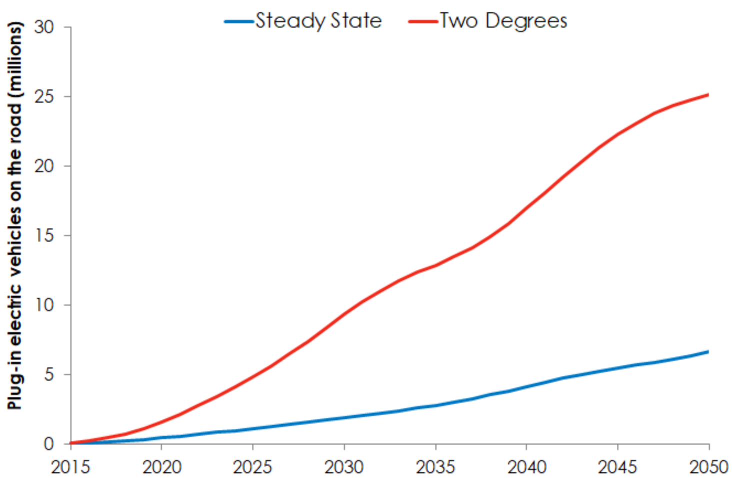


Figure C.16: Projected number of electric vehicles on the road in Great Britain under Steady State and Consumer Power scenarios. Source: (National Grid, 2017a; BEIS, 2017c)



Appendix D

Creating consumer agents

D.1 Allocating consumer numbers to consumer agents

When the model run is initialised in step R0 of the algorithm shown in Figure 3.9, the environment creates consumer agents, i.e. $n^{sec}_{type}, \quad \forall sec \in \mathscr{S}, type \in \{type1, ..., type10\}$. This step is performed only once during the run. The allocation of consumers is done at the beginning of each of the run, as this is when the global parameters for technology capacities change.

The information of how many real consumers each agent represents is conveyed by the consumer multiplier numbers shown in Table D.1. In addition to this the model is operated in megawatts rather than kilowatts and so we make it simpler by making the smallest unit of consumer multiplier 1000 consumers which automatically convert all kilowatt values into MW.

The number of consumers of each type within each sector as shown in Table 3.3 changes depending on the scenario and the year of simulation. For example, the National Grid projects the number of domestic consumers with electrical storage of capacity 3kW (average) to reach 710,000 by 2050 in their Future Energy Scenarios (FES) under high penetration case (assuming an equal split of storage between residential, commercial and industrial sectors). Some of those consumers will be of type 8 and not have any other resources, however a proportion will be of types 7, 9 and 10. Now, the number of consumers of type 7 is constrained by the number

Table D.1: Allocation of consumer multipliers.

Consumer type \ Sector	Domestic	Commercial	Industrial	Transport
1 (no resources)	m^{dom}_{type1}	m^{com}_{type1}	m^{ind}_{type1}	-
2 (with HP)	m^{dom}_{type2}	m^{com}_{type2}	m^{ind}_{type2}	-
3 (with HP and TES)	m^{dom}_{type3}	m^{com}_{type3}	m^{ind}_{type3}	-
4 (with RH)	m^{dom}_{type4}	m^{com}_{type4}	m^{ind}_{type4}	-
5 (with RH and TES)	m^{dom}_{type5}	m^{com}_{type5}	m^{ind}_{type5}	-
6 (with PV)	m^{dom}_{type6}	m^{com}_{type6}	m^{ind}_{type6}	-
7 (with PV and ES)	m^{dom}_{type7}	m^{com}_{type7}	m^{ind}_{type7}	-
8 (with ES)	m^{dom}_{type8}	m^{com}_{type8}	m^{ind}_{type8}	m^{trans}_{type8}
9 (with HP,PV,TES,ES)	m^{dom}_{type9}	m^{com}_{type9}	m^{ind}_{type9}	-
10 (with RH,PV,TES,ES)	m^{dom}_{type10}	m^{com}_{type10}	m^{ind}_{type10}	-

Key: HP - heat pump, RH - resistance heater, PV - solar photovoltaic, TES - thermal energy store, ES - electrical store.

domestic consumers with solar PV in the system projected to reach 3.2 million by 2050 in accordance with the FES, whilst the number of consumers of types 9 and 10 are also constrained by the availability of heat pumps (1.2 million), thermal storage (8.2 million) and resistance heating (2.7 million) in the system. The total number of domestic consumers of all types must equal to 36.5 million (calculated based on total non-thermal electricity consumption in 2050) making the process of allocating consumer numbers non-trivial. Coupled with an additional constraint of there being at least 1 agent of each type (required to assess the impact of system dynamics on all consumer types) makes the process of allocating consumers to each type becomes non-trivial.

The model allocates consumers at the beginning of each run by minimising the difference between the number of actual projected technologies ($N^{sec,tech}_{act}$) (taken from FES or other available sources) and the technology number modelled in ESMA ($N^{sec,tech}_{mod}$)[1]

[1]The reason, we do not look for exact numbers is because at times the problem is not solvable taking into account all technology value constraints. A correction factor introduced slightly later

$$\min \sum_{sec \in \mathscr{S}} \sum_{tech \in \mathscr{T}} (N_{mod}^{sec,tech} - N_{act}^{sec,tech})^2, \tag{D.1}$$

where $\mathscr{T} = \{\mathrm{ES}, \mathrm{TES}, \mathrm{HP}, \mathrm{RH}, \mathrm{PV}, \mathrm{tot}\}$ is a set of all technology types and $\mathscr{S} = \{\mathrm{dom}, \mathrm{com}, \mathrm{ind}, \mathrm{trans}\}$ is a set of all consumer sectors.

The above problem is constrained by the availability of technology within each sector and across all type of consumers. Hence, the total domestic electrical storage will be spread across domestic consumers of types 7, 8, 9 and 10. So, $n_{mod}^{dom,ES} = m_{type7}^{dom} + m_{type8}^{dom} + m_{type9}^{dom} + m_{type10}^{dom}$.

The constraints are summarised as follows:

$$\begin{aligned}
n_{mod}^{sec,ES} &= m_{type7}^{sec} + m_{type8}^{sec} + m_{type9}^{sec} + m_{type10}^{sec}, \\
n_{mod}^{sec,TES} &= m_{type3}^{sec} + n_{type5}^{sec} + n_{type9}^{sec} + n_{type10}^{sec}, \\
n_{mod}^{sec,HP} &= n_{type2}^{sec} + n_{type3}^{sec} + n_{type9}^{sec}, \\
n_{mod}^{sec,RH} &= n_{type4}^{sec} + n_{type5}^{sec} + n_{type10}^{sec}, \\
n_{mod}^{sec,PV} &= n_{type6}^{sec} + n_{type7}^{sec} + n_{type9}^{sec} + n_{type10}^{sec}, and \\
n_{mod}^{sec,tot} &= n_{type1}^{sec} + n_{type2}^{sec} + n_{type3}^{sec} + n_{type4}^{sec} + n_{type5}^{sec} + \\
& \quad n_{type6}^{sec} + n_{type7}^{sec} + n_{type8}^{sec} + n_{type9}^{sec} + n_{type10}^{sec} \quad \forall sec \in \mathscr{S}.
\end{aligned}$$

The model solves the above minimisation problem for n_{type}^{sec}, $\forall sec \in \mathscr{S}, \forall \quad type \in \{type1, ..., type10\}$. We refer to the consumer number for each type n_{type}^{sec} as consumer multiplier.

For domestic consumers in the Two Degrees+ scenario we introduce a linear efficiency improvement for domestic appliances as per National Grid's scenarios which assume a 30% improvement by 2030.

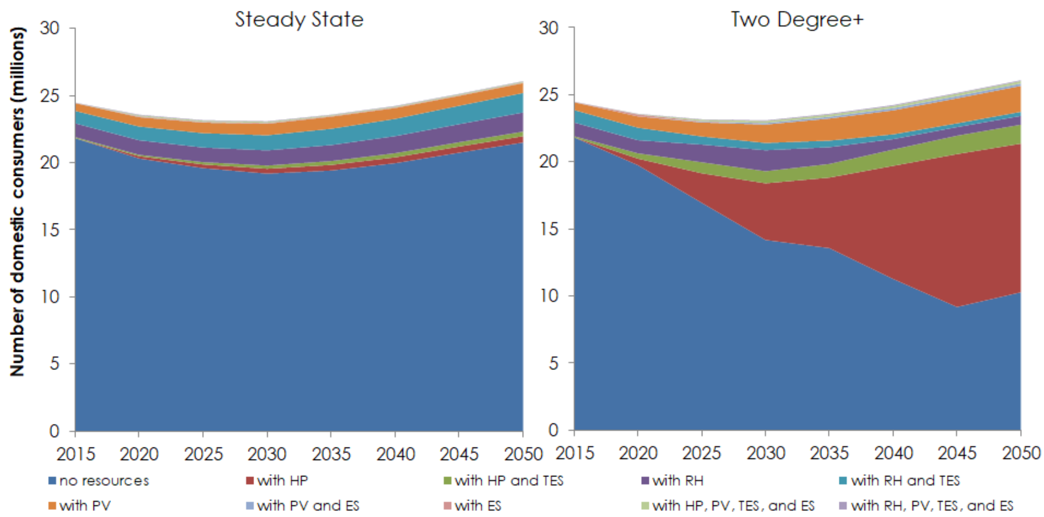
corrects for the slight deviation.

D.1.1 Consumer numbers

The following charts demonstrate how the consumer allocation method described in D.1 works in calculating the number of consumers for each type and sector. We compare the two scenarios considered in this work Steady State and the Two Degrees+ .

It can be seen how the share of consumers with no resources reduces over time for the Two Degrees+ scenario, whilst under Steady scenario the share of different consumers stays fairly consistent. This is expected as consumer are obtaining more distributed energy resources such as solar PV, storage and electric heating. The change is more pronounced for the domestic consumers compared to commercial and industrial sectors, where by 2040 the model project no consumers without resources (Figure D.1).

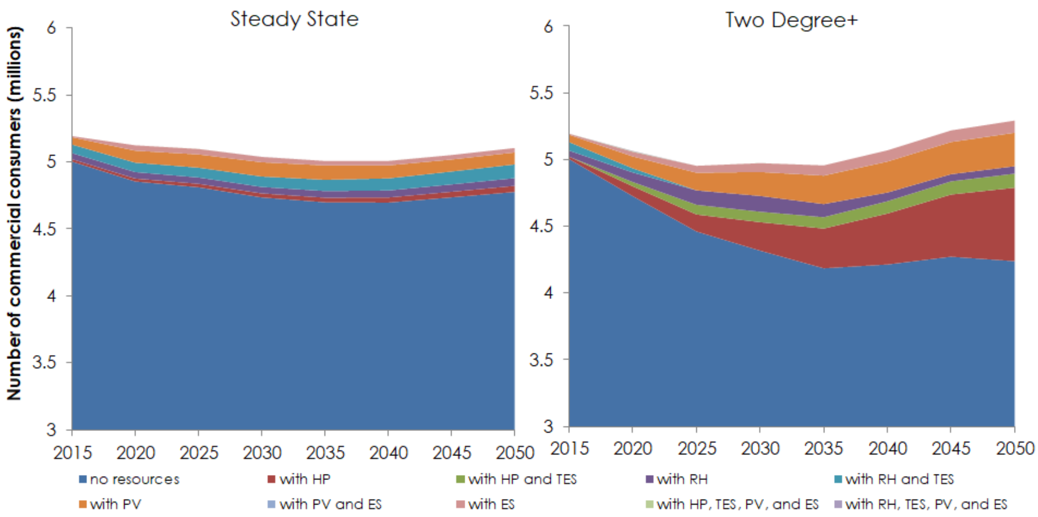
Figure D.1: Demonstration of consumer allocation for domestic sector.



For commercial sector there is still a considering number of consumers with no resources under Two Degrees+ scenario with the number dropping to around 4.4 million by 2035. Again we can see how the share of consumers with electric heating and storage increases over time. This is especially true for consumer with heat pumps and thermal storage (in green) and for consumers with electric storage (in orange) (Figure D.2).

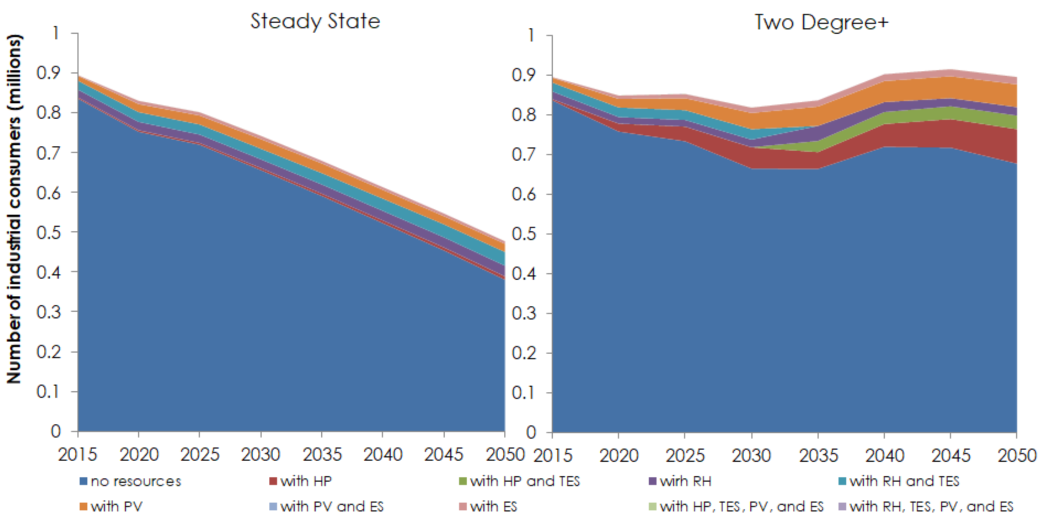
For industrial sector we note that under Steady state scenario the number of

Figure D.2: Demonstration of consumer allocation for commercial sector.



consumers drops, whilst under Two Degrees+ it stays fairly consistent (Figure D.3).

Figure D.3: Demonstration of consumer allocation for industrial sector.

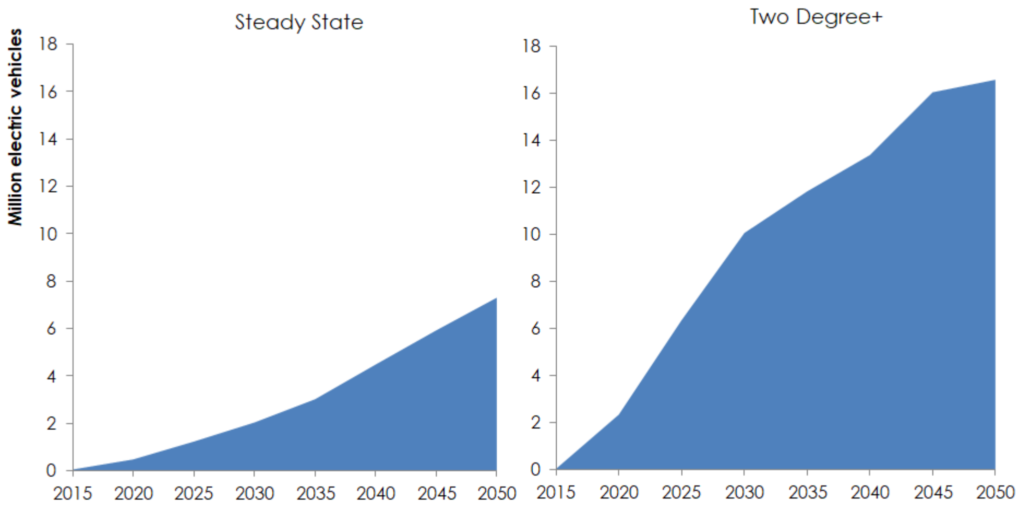


Transportation sees a significantly larger number of electric vehicles under Two Degrees+ scenario (Figure D.4).

Once the environment has set the day and the year of the simulation consumer adjust capacities for all their resources based on the consumer allocation number calculated in step E0.

Although the number of consumers varies throughout the length of the run,

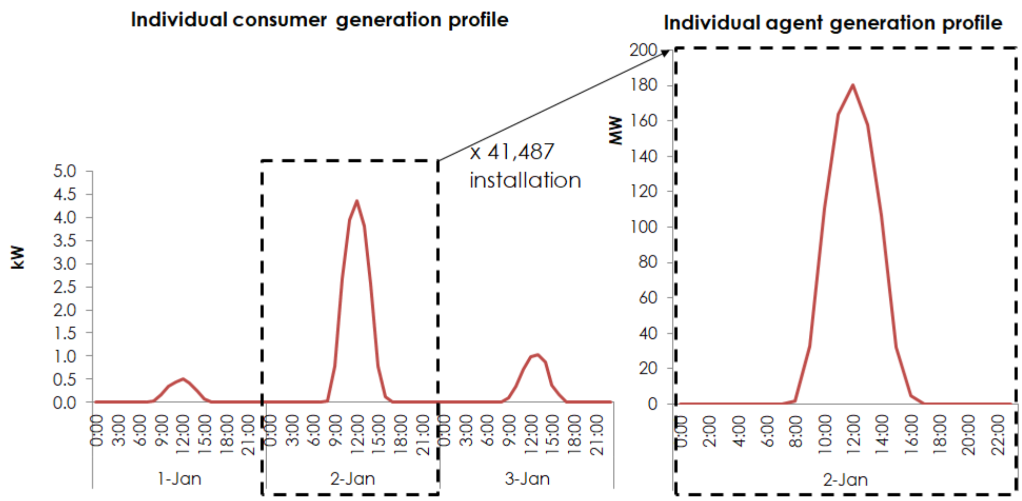
Figure D.4: Demonstration of consumer allocation for transport sector.



the number of agents does not change from what has been set in step R0. Hence, there might be 50,000 consumers of type 3 (in possession of HP and TES) but the model will only have 1 modelled agent representing all of them. Hence, when the consumer sets technological capacities at the beginning of the run, it multiplies individual technology capacity by the consumer multiplier number since it represents the number of technological units belonging to this agent type. For example, if there are 50,000 domestic consumers of type 3, then the HP capacity for one domestic consumer agent of type 3 is calculated as the individual HP capacity 2 kW multiplied by the consumer multiplier 50,000 resulting in the aggregate capacity of 100 MW.

Applying consumer multipliers allows to keep the number of modelled technologies in-line with FES scenario. For example, during daily initialisation step C1 (Figure 3.9) consumers predict renewable generation by selecting the relevant daily generation profile from the annual generation data. They then scale the daily profile by the consumer multiplier set in C0. Hence, if a consumer agent representing 41,487 commercial consumers with solar is prediction generation for the 2nd January 2015 it will select the daily generation profile for the 2nd of January and multiply it by 41,487 as shown in Figure D.5. We assume no uncertainty in consumer agents predicting renewable generation.

Figure D.5: Projected installed solar capacity in Great Britain at distribution level. Source: (National Grid, 2017a).



Appendix E

Model calibration

E.1 Wholesale prices calibration

As discussed in section 3.4.5.3, in the context of ESMA electricity generators schedule based on the simplified least-cost dispatch model. However, this underestimates the true level of wholesale electricity prices. Here, a method of uplifting the electricity prices to a more representative level is introduced. The modelled uplift $\varepsilon(t,d)$ represents any additional costs incurred in generating and delivering electricity to end-users such as the costs for utilising the transmission and distribution network as well as balancing.

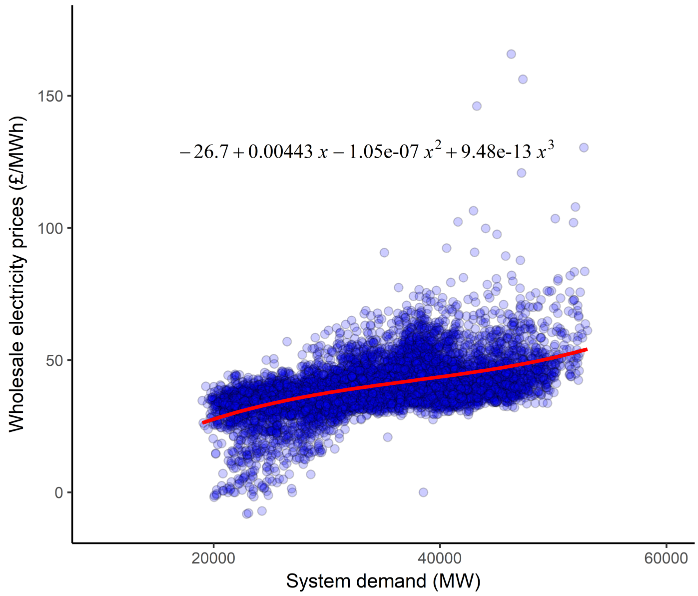
Hence, the final wholesale price in time t and day d consist of a short run component $p_{SR}(t,d)$ and a demand dependent uplift $\varepsilon(t,d)$ is not modelled:

$$p(t,d) = p_{SR}(t,d) + \varepsilon(t,d), \quad \forall t \in [1,T]. \tag{E.1}$$

In order to calculate the uplift we use historical data for wholesale prices taken from the exchange (Figure E.1). As can be seen from the figure the data is very noisy. It is expected, since exchange trades include deals for short term delivery some of which are not for physical delivery but rather speculative. In order to reduce the noise we fit a polynomial to obtain the historical relationship between demand and wholesale price level as shown on the chart.

We then use the relationship between historical demand and prices in order to calculate the residual prices, i.e. the difference between historical and prices

Figure E.1: Historical electricity prices vs system demand, Jan-Dec (APX Group, 2015)



modelled in ESMA. In the final step we fit a polynomial to the residual prices, which determines the uplift calculations.

The left chart in Figure E.2 shows the prices output from the model as well as the prices according to the historical relationship. The chart on the right shows the residual prices as well as the equation for calculating the uplift, i.e.

$$\varepsilon(t,d) = -51.3 + 0.00601 \cdot L(t,d) - 1.51 \cdot 10^{-7} L^2(t,d) + 1.51 \cdot 10^{-12} L^3(t,d), \tag{E.2}$$

where $L(t,d)$ is the system demand in time t and day d.

Adding the uplift to the modelled prices according to (E.1) renders the final wholesale prices in ESMA. Figure E.3 shows how the modelled prices compare to historical values for the base year 2015. We note that historical relationship is only available for demand higher than 21GW and so for demand below this value we model the uplift as a linear function guided by the assumption that at zero demand the cost of utilising the grid is zero.

We acknowledge that the equation for the uplift is calibrated against a historical 2015 year and that it will likely change in the future. In order to adjust the uplift to future years we consult the Future Energy Scenarios (FES) provided by (National

Figure E.2: Modelled electricity prices.

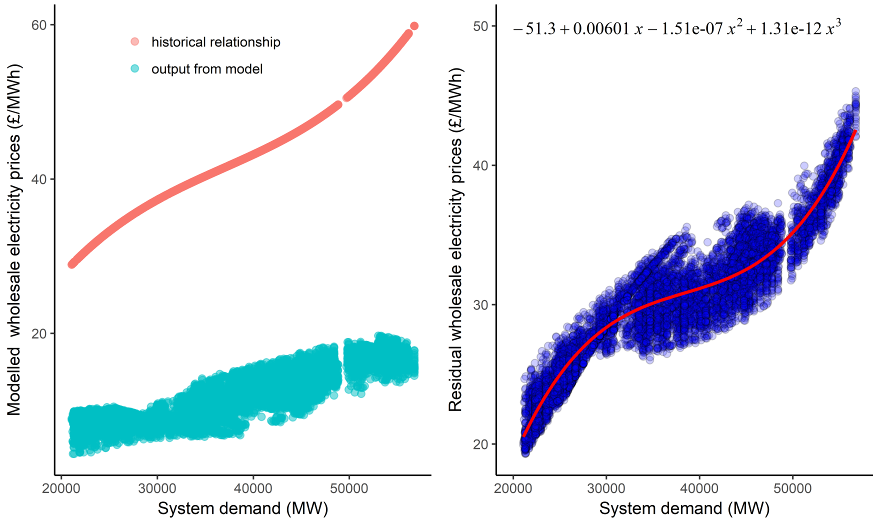
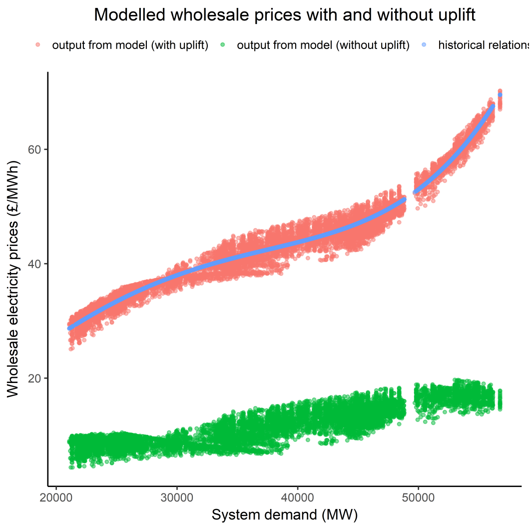


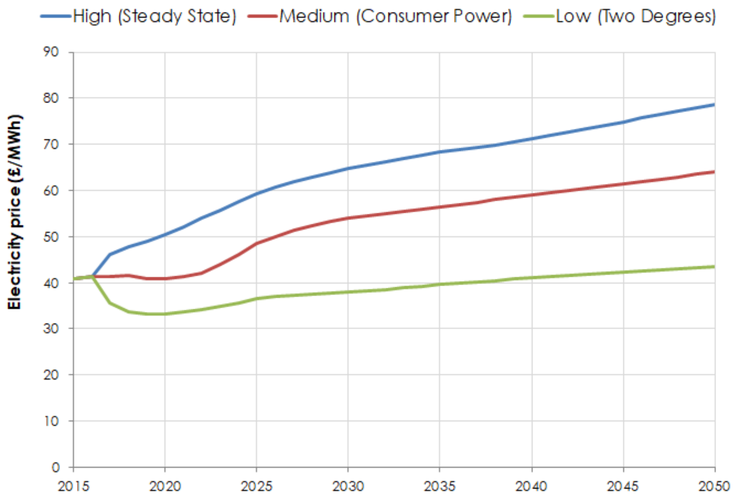
Figure E.3: Modelled electricity prices.



Grid, 2017a), which offer an average electricity price level for baseload generation. Figure E.4 demonstrates how baseload electricity prices are projected to change under different national scenarios.

We use this information about prices to adjust the uplift relationship on system demand determined earlier. For Two Degrees+ we select the medium case, since it is a combination of the Two Degrees and Consumer Power scenarios. In addition this we expect that as the level of renewable generation increases a high proportion of the price will come from the capital costs, which are not modelled in ESMA. We

Figure E.4: Projected electricity prices. Source: (National Grid, 2017a)



compensate for this by choosing the higher uplift scenario from the medium and low cases. Figure E.5 demonstrates how the uplifts change throughout the years and Figure E.6 shows the final wholesale prices modelled in ESMA.

Figure E.5: Projected wholesale price uplift curves. Source: own modelling.

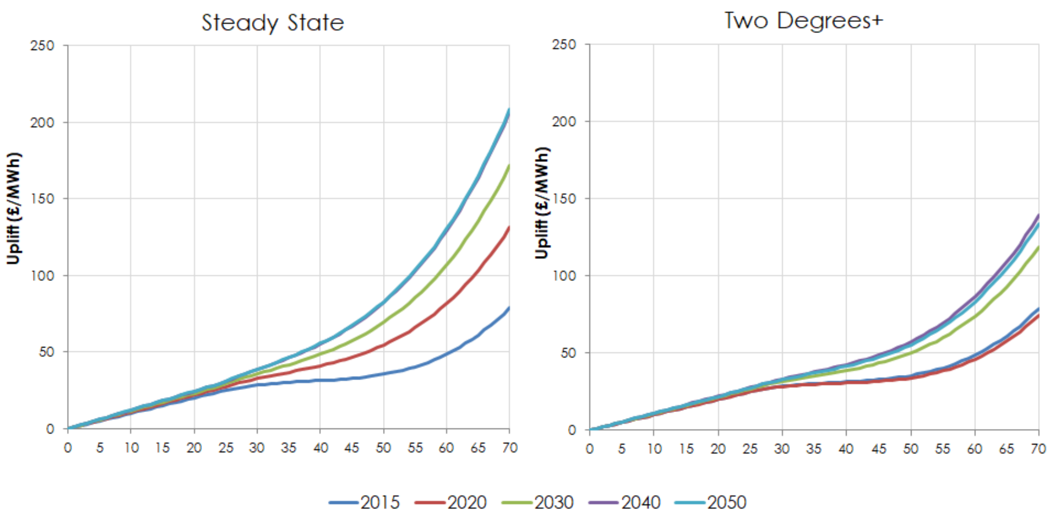
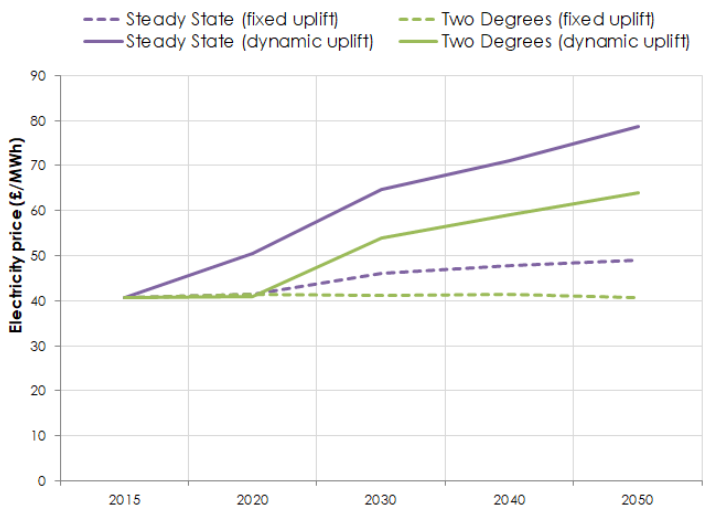


Figure E.6: Projected wholesale electricity prices in the base case (no coordination). Source: ESMA.



E.2 Demand side response algorithms

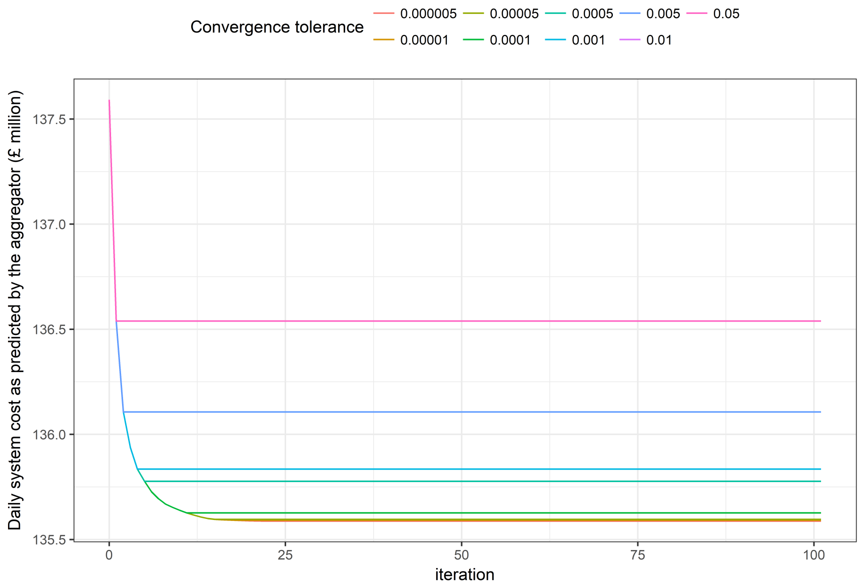
Since the demand side algorithm used in this work have been adapted from the original it was important to set the right tolerance level ε for their convergence and the damping term α. The primary concern when setting these parameters was to balance speed and accuracy of the simulation. The following section describes the reasoning behind setting these parameters.

E.2.1 Aggregator DSM algorithm: AGG_DF and AGG_CM

Algorithm AGG_DF has been taken almost directly from the original one proposed by (Gan et al., 2013). So for this algorithm it was important to set the tolerance level ε at which it was decided that the algorithm converges. Figure E.7 shows how the cost at each iteration changes when we set a different tolerance level. For the purpose of the demonstration we run the simulation for one winter day in 2050 (Steady State). It is possible to see that when the level of tolerance level ε is higher the algorithm converges quicker but the total system cost is higher.

We select the appropriate tolerance level by looking at the time it takes for the algorithm to run daily as well as the accuracy at each value (Figure E.8). Looking at the time it takes for the simulation to complete one day and the marginal benefit of decreasing the tolerance level brings to reducing the system cost, we select tolerance

Figure E.7: Demonstration of the convergence of algorithm AGG_DF, 1 Jan 2050 (Steady State). Source: ESMA.



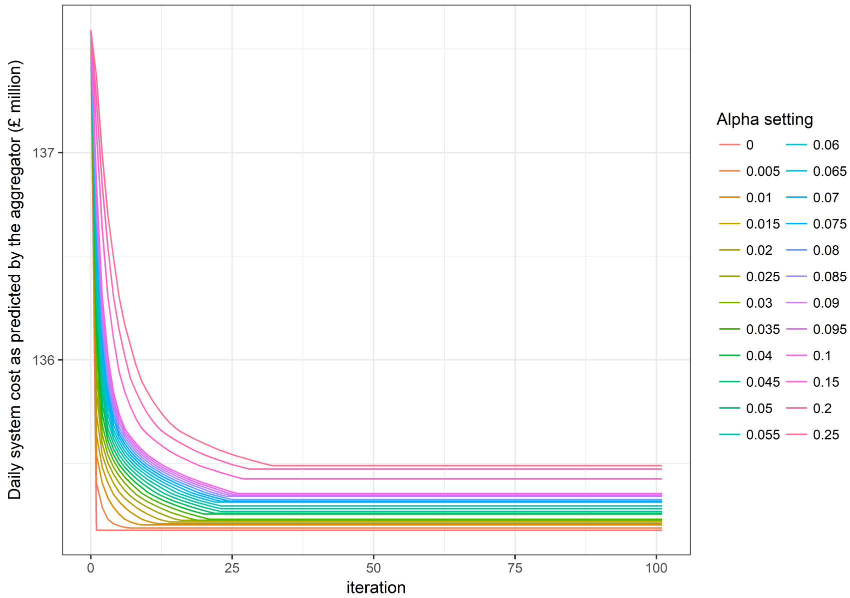
of 0.005%. We justify this choice by the fact that running the simulation for more than 45 minutes per year would take too long to complete at least two scenarios and three years of simulation, especially considering that the marginal benefit of reducing cost is 0.004%.

Figure E.8: Analysis of convergence time and accuracy of algorithm AGG_DF with different level of tolerance, 1 Jan 2050 (Two Degrees+). Source: ESMA.

Convergence tolerance	Number of iteration to converge	Time taken per day (s)	Time taken per year (mins)	System cost (£ million)	Marginal reduction in cost
0.000005	22	9.68	58.87	135.59	-0.003%
0.00001	18	7.51	45.68	135.59	-0.004%
0.00005	15	6.45	39.22	135.60	-0.022%
0.0001	11	5.02	30.52	135.63	-0.111%
0.0005	5	2.79	16.95	135.78	-0.043%
0.001	4	2.30	14.01	135.83	-0.200%
0.005	2	1.43	8.72	136.11	-0.317%
0.01	1	0.88	5.38	136.54	0.000%
0.05	1	0.89	5.43	136.54	

For AGG_CM it has been found that the algorithm performs best when the penalty term is set to 0 meaning that consumers are instructed to maximise shifting demand towards periods of low electricity prices (Figure E.9). For all the other setting of α, the algorithm converged to a higher cost.

Figure E.9: Demonstration of the convergence of algorithm AGG_DF, 1 Jan 2050 (Steady State). Source: ESMA.



E.2.2 System Operator cost minimising algorithm (SO_CM)

For SO_CM the tolerance level has been kept at the same level as for AGG_DF to ensure fairness when comparing different regimes. However, we found that it was necessary to adjust the damping term α. Figure E.10 demonstrates how the algorithm reduces the system cost as α is varied between 0 and 1. Similarly to the case of AGG_DF α is selected based on the system cost and the convergence time of the algorithm (Figure E.11). In fact only with $\alpha = 0.05$ does the algorithm converge in a reasonable time.

However it turns out that the algorithm is quite sensitive to this parameters as can be seen in Figure E.12 where the algorithm is run across different years and scenarios. On the whole the model is more sensitive to the lower values of alpha (<0.02), however the sensitivity changes depending on the year of the simulation. This happens because unlike algorithm AGG_DF (where the signal is based on the average aggregate consumer demand) in SO_CM it is the price which itself depends on the system demand and generation resources in the system. Hence it is of no surprise that the optimal damping parameter setting has to be adjusted daily.

Figure E.10: Demonstration of SO_CM algorithm convergence under different values of α, 1 Jan 2050 (Steady State).

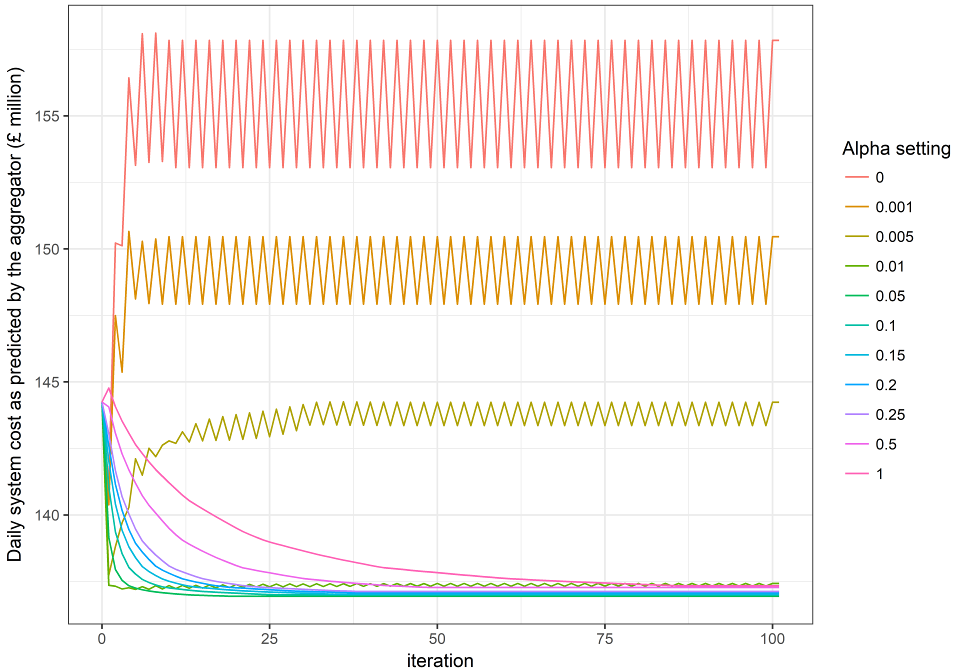
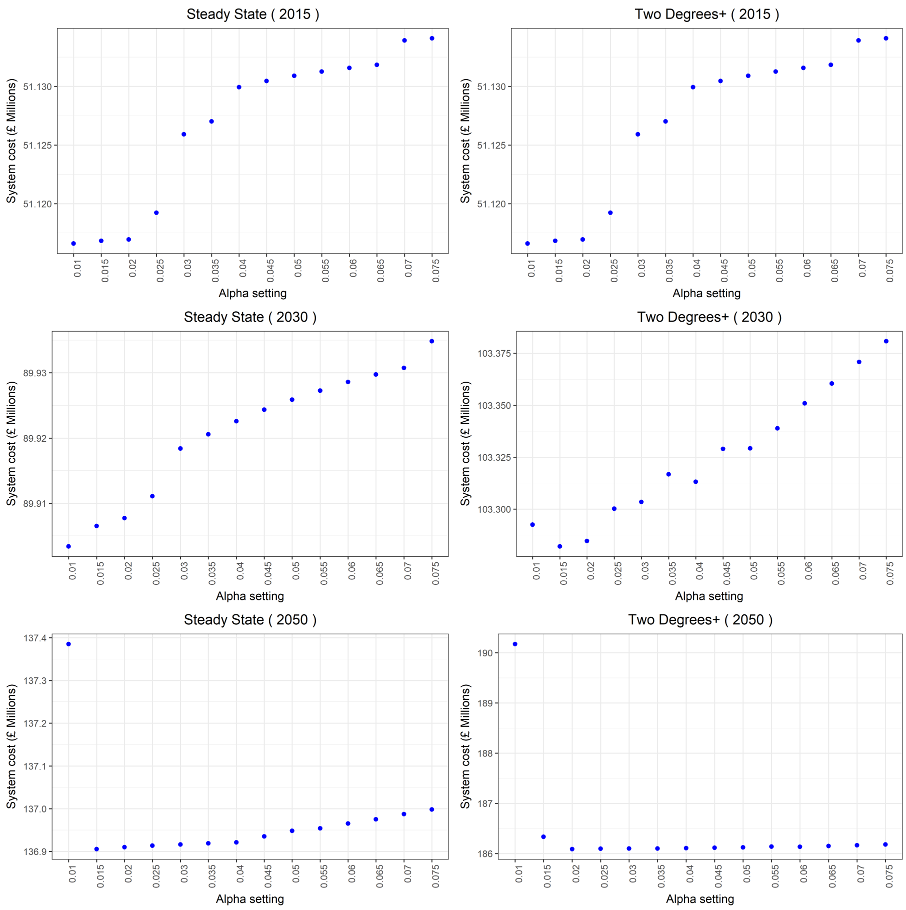


Figure E.11: Analysis of convergence time and accuracy of algorithm SO_CM with different α setting, 1 Jan 2050 (Two Degrees+). Source: ESMA.

Alpha setting	Number of iteration to converge	Time taken per day (s)	Time taken per year (mins)	System cost (£ million)	Marginal reduction in cost
0	does not converge	42.00	255.50	157.84	4.903%
0.001	does not converge	43.00	261.58	150.46	4.314%
0.005	does not converge	47.40	288.35	144.24	4.954%
0.01	>100	44.90	273.14	137.43	0.352%
0.05	19	8.40	51.10	136.95	-0.035%
0.1	27	12.00	73.00	137.00	-0.015%
0.15	36	15.80	96.12	137.02	-0.045%
0.2	37	16.40	99.77	137.08	-0.036%
0.25	38	16.70	101.59	137.13	-0.109%
0.5	49	22.00	133.83	137.28	-0.046%
1	86	40.00	243.33	137.34	

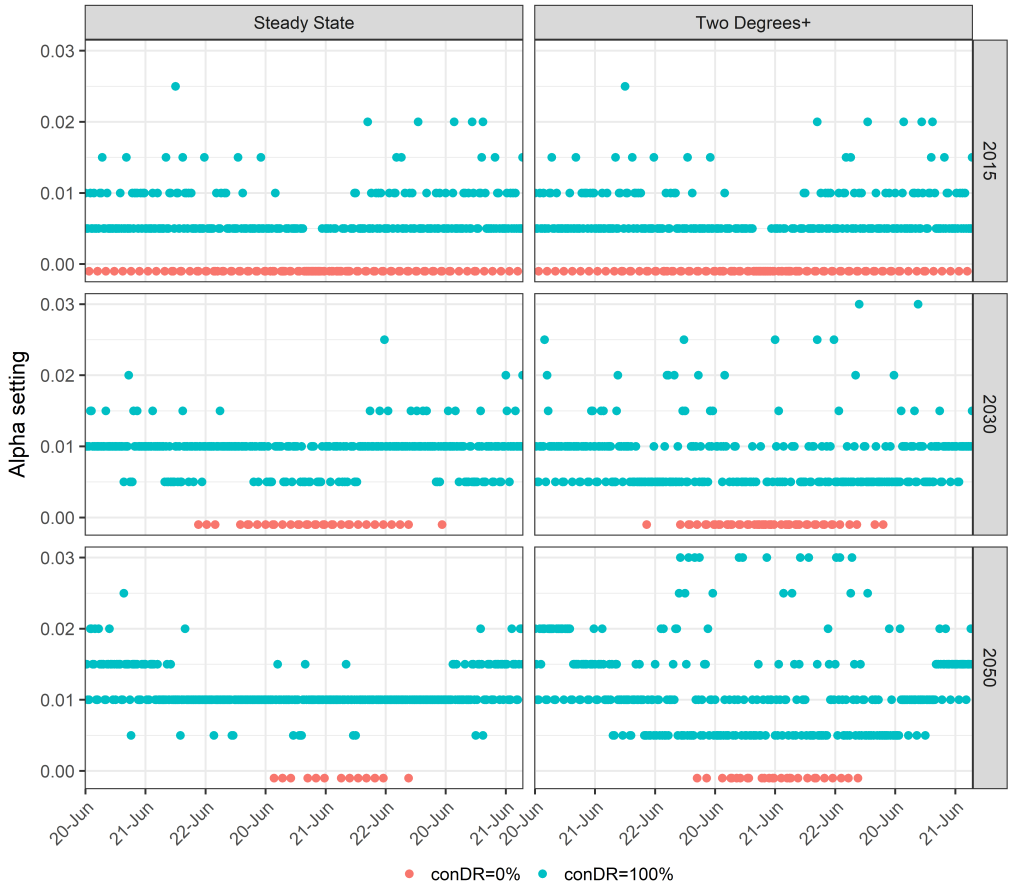
In order to consider the full potential of algorithm SO_CM the simulation is run for a range of α settings and select those days with the lowest system cost as demonstrated in Figure E.13. It is noted that the value of alpha for which the algorithm achieves the lowest cost varies depending on the day, which is of no surprise since system prices and demand change throughout the year. In addition to this, on certain days the system does better when consumers do not coordinate at all (red points). This situation happens during the days when the price curve is steep

Figure E.12: Sensitivity of system cost to the α setting on the 1st January in 2015, 2030 and 2050 in the Steady State and Two Degrees+.



meaning that increasing demand from operating storage is not justified by making savings from a reduction in price peaks. Looking at the pattern for consumer exports (Figure E.14) it is possible to see that it appears to inversely mimic the pattern for best α setting (with an exception of a few outliers). This suggests that the higher the amount of renewables and the lower the prices, the lower is the optimal setting for α. This relationship also confirms our explanation for why on certain days the system does better without DSM, i.e. when renewable generation is high the price curve is shallow and so DSM carries less value in comparison to the higher cost which comes from operating storage.

Figure E.13: Alpha settings which lead to the least system cost on the daily basis in 2015, 2030 and 2050 in the Steady State and Two Degrees+.



E.3 Consumer learning algorithm for α

When choosing settings for conStep and conExplore, we perform sensitivity analysis of the model to these two parameters and select the combination which leads to the least system cost. We focus on the year 2050 in Two Degrees+ since it is the year which saw the highest level of herding.

Figure E.15 shows the level of system cost achieved under different combination of step size and exploration rate of consumer, which can be identified by the shade of the square. It is possible to see that the system achieves the lowest cost when conExplore=0.5 and conStep=0.005 which corresponds to the situation when the consumer explores 50%. Hence, these values are chosen as the default setting for the learning algorithm in our model. When step size is too small, the consumer fails to converge to the optimal value of α^c in time, whereas when step size is too

Algorithm 6: Consumer algorithm for learning α.

Input : Consumer c knows today's electricity prices $p(t,d)$, own net demand $l^c_{net}(t,d)$ and own $\alpha^c(d)$ and yesterday's cost for purchased electricity $z^c(d-1)$ and $\alpha(d-1)$.

Output: Damping term for day ahead $\alpha^c(d+1)$

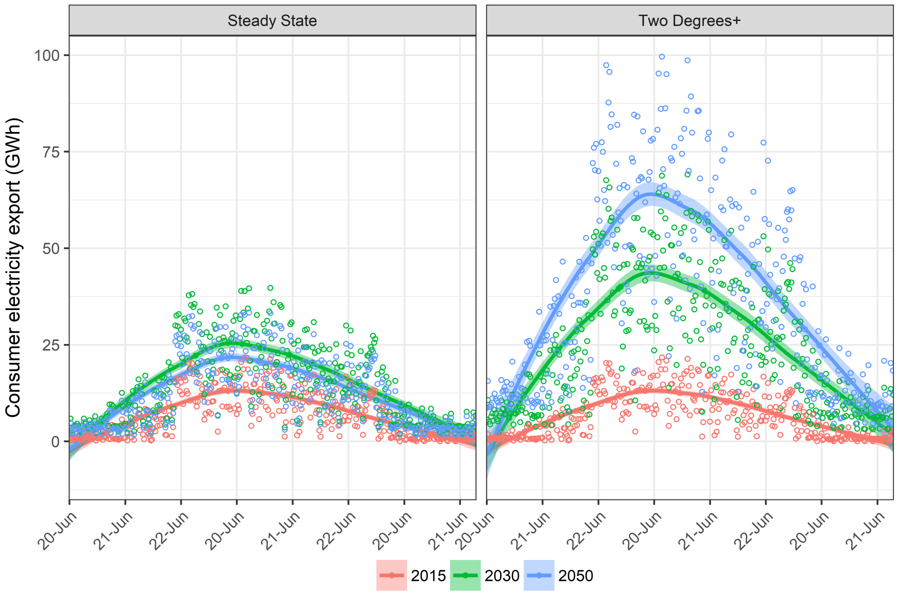
. Consumer calculates the cost of purchase electricity in day d:

$$z^c(d) = \sum_{t=1}^{T} p(t,d) \cdot l^c_{net}(t,d)$$

if $z^c(d) > z^c(d-1)$ **then**
    $\alpha^c(d+1) = \alpha^c(d-1)$;
end
else
    if $Random[0,1] < conExplore$ **then**
        if $Random[0,1] < 0.5$ **then**
            $\alpha^c(d+1) = \alpha^c(d) + conStep$;
        end
        else
            $\alpha^c(d+1) = \alpha^c(d) - conStep$;
        end
    end
    else
        do nothing;
    end
end
Consumer updates yesterday's α and cost:

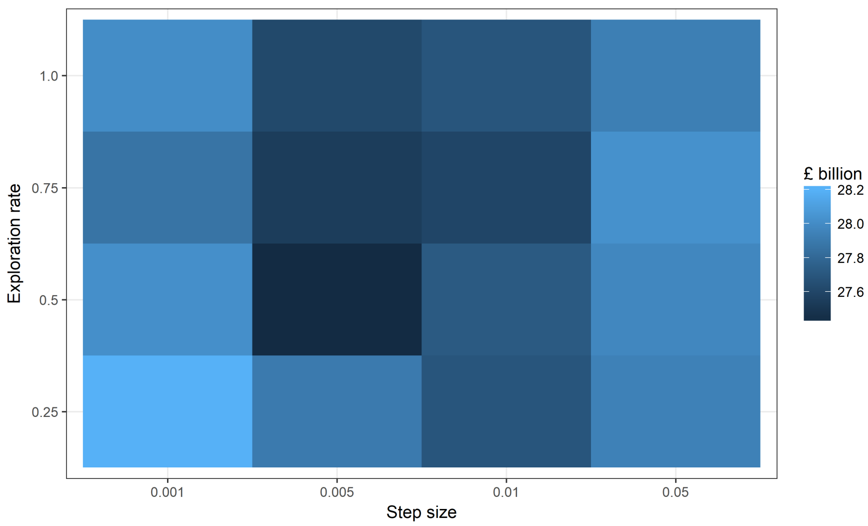
$$z^c(d-1) = z^c(d), \alpha(d-1) = \alpha(d)$$

Figure E.14: Daily consumer exports in 2015, 2030 and 2050 in the Steady State and Two Degrees+.



large it is easy for consumer to overshoot. When the exploration rate is too small, the consumer fails to progress with finding an optimal value of α, whereas when the exploration rate is too large the consumer does not stick with α^c which leads to lower cost.

Figure E.15: Sensitivity of system cost to values of conExplore and conStep, 2050 (Two Degrees+).



Appendix F

Data tables

Figure F.1: Annual consumer electricity demand and cost in the base case by sector, 2015-2050. Source: ESMA

	Sector	Domestic		Commercial		Industrial		Transport	
Scenario	Year	Annual consumption (TWh)	Annual electricity bill (£ million)	Annual consumption (TWh)	Annual electricity bill (£ million)	Annual consumption (TWh)	Annual electricity bill (£ million)	Annual consumption (TWh)	Annual electricity bill (£ million)
Base year	2015	114.5	4,938.8	97.0	4,243.6	94.7	4,126.2	0.11	4.503
Steady State	2030	116.7	8,074.1	96.4	6,724.0	86.4	5,968.9	4.3	276.8
	2050	136.7	12,069.2	101.2	8,855.6	72.7	6,280.4	15.5	1,201.3
Two Degrees+	2030	112.0	6,874.7	102.7	6,033.8	99.1	5,718.0	21.3	1,136.7
	2050	116.5	9,580.9	113.3	8,166.6	103.6	7,222.8	35.0	2,197.5

Figure F.2: Annual consumer electricity consumption and cost in the base case by type in the Steady State scenario, 2015-2050. Source: ESMA

Sector	Metric	year \ type	with no resources	with HP	with HP and TES	with RH	with RH and TES	with PV	with PV and ES	with ES	with HP,PV,TES and ES	with RH,PV,TES and ES
Domestic	Annual electricity bill (£)	2015	153.4	365.9	365.9	791.2	791.2	(2.7)	(2.7)	153.4	209.8	635.1
		2030	242.4	603.7	603.7	1,321.4	1,321.4	(0.7)	(0.7)	242.4	360.6	1,078.2
		2050	298.0	774.5	774.5	1,714.5	1,714.5	6.1	6.1	298.0	482.6	1,422.6
	Annual electricity consumption (MWh)	2015	3.5	8.1	8.1	17.4	17.4	3.5	3.5	3.5	8.1	17.4
		2030	3.5	8.1	8.1	17.4	17.4	3.5	3.5	3.5	8.1	17.4
		2050	3.5	8.1	8.1	17.4	17.4	3.5	3.5	3.5	8.1	17.4
Commercial	Annual electricity bill (£)	2015	730.7	2,142.2	2,142.2	5,054.2	5,054.2	(119.5)	(119.5)	730.7	1,291.9	4,204.0
		2030	1,170.4	3,509.5	3,509.5	8,298.7	8,298.7	(154.0)	(154.0)	1,170.4	2,185.1	6,974.3
		2050	1,450.1	4,460.7	4,460.7	10,573.9	10,573.9	(140.0)	(140.0)	1,450.1	2,870.6	8,983.8
	Annual electricity consumption (MWh)	2015	16.6	47.7	47.7	112.3	112.3	16.6	16.6	16.6	47.7	112.3
		2030	16.6	47.7	47.7	112.3	112.3	16.6	16.6	16.6	47.7	112.3
		2050	16.6	47.7	47.7	112.3	112.3	16.6	16.6	16.6	47.7	112.3
Industrial	Annual electricity bill (£)	2015	3,513.5	11,062.9	11,062.9	27,425.3	27,425.3	(196.0)	(196.0)	3,513.5	7,353.5	23,715.8
		2030	5,608.1	17,912.3	17,912.3	44,297.6	44,297.6	(170.0)	(170.0)	5,608.1	12,134.2	38,519.5
		2050	6,934.7	22,458.1	22,458.1	55,362.9	55,362.9	(2.6)	(2.6)	6,934.7	15,520.9	48,425.6
	Annual electricity consumption (MWh)	2015	80.0	248.4	248.4	617.1	617.1	80.0	80.0	80.0	248.4	617.1
		2030	80.0	248.4	248.4	617.1	617.1	80.0	80.0	80.0	248.4	617.1
		2050	80.0	248.4	248.4	617.1	617.1	80.0	80.0	80.0	248.4	617.1
Transport	Annual electricity bill (£)	2015								88.1		
		2030								135.9		
		2050								164.4		
	Annual electricity consumption (MWh)	2015								2.1		
		2030								2.1		
		2050								2.1		

Figure F.3: Annual consumer electricity consumption and cost in the base case by type in the Two Degrees+ scenario, 2015-2050. Source: ESMA

Sector	Metric	year \ type	with no resources	with HP	with HP and TES	with RH	with RH and TES	with PV	with PV and ES	with ES	with HP,PV,TES and ES	with RH,PV,TES and ES
Domestic	Annual electricity bill (£)	2015	153.4	365.9	365.9	791.2	791.2	(2.7)	(2.7)	153.4	209.8	635.1
		2030	142.9	475.0	475.0	1,128.1	1,128.1	(34.3)	(34.3)	142.9	297.8	950.9
		2050	115.2	563.7	563.7	1,435.4	1,435.4	(74.2)	(74.2)	115.2	374.3	1,246.0
	Annual electricity consumption (MWh)	2015	3.5	8.1	8.1	17.4	17.4	3.5	3.5	3.5	8.1	17.4
		2030	2.5	7.1	7.1	16.3	16.3	2.5	2.5	2.5	7.1	16.3
		2050	1.7	6.3	6.3	15.5	15.5	1.7	1.7	1.7	6.3	15.5
Commercial	Annual electricity bill (£)	2015	730.7	2,142.2	2,142.2	5,054.2	5,054.2	(119.5)	(119.5)	730.7	1,291.9	4,204.0
		2030	975.2	3,065.3	3,065.3	7,285.5	7,285.5	9.8	9.8	975.2	2,099.9	6,320.1
		2050	1,174.4	3,862.5	3,862.5	9,209.2	9,209.2	142.8	142.8	1,174.4	2,830.8	8,177.5
	Annual electricity consumption (MWh)	2015	16.6	47.7	47.7	112.3	112.3	16.6	16.6	16.6	47.7	112.3
		2030	16.6	47.7	47.7	112.3	112.3	16.6	16.6	16.6	47.7	112.3
		2050	16.6	47.7	47.7	112.3	112.3	16.6	16.6	16.6	47.7	112.3
Industrial	Annual electricity bill (£)	2015	3,513.5	11,062.9	11,062.9	27,425.3	27,425.3	(196.0)	(196.0)	3,513.5	7,353.5	23,715.8
		2030	4,669.4	15,246.2	15,246.2	37,513.7	37,513.7	457.5	457.5	4,669.4	11,034.3	33,301.8
		2050	5,608.8	18,752.7	18,752.7	45,840.3	45,840.3	1,107.7	1,107.7	5,608.8	14,251.7	41,339.3
	Annual electricity consumption (MWh)	2015	80.0	248.4	248.4	617.1	617.1	80.0	80.0	80.0	248.4	617.1
		2030	80.0	248.4	248.4	617.1	617.1	80.0	80.0	80.0	248.4	617.1
		2050	80.0	248.4	248.4	617.1	617.1	80.0	80.0	80.0	248.4	617.1
Transport	Annual electricity bill (£)	2015								88.1		
		2030								112.9		
		2050								132.6		
	Annual electricity consumption (MWh)	2015								2.1		
		2030								2.1		
		2050								2.1		

Appendix G

Colophon

☐ This document was set in the Times New Roman typeface using LaTeX and BibTeX, composed with a text editor.

☐ The model was developed in Repast Simphony-2.3.1 using the JAVA programming language.

☐ Linear programming was implemented using IBM's ILOG CPLEX 12.6.

☐ Figures and tables were created Rstudio with R-3.4.3 and Microsoft Excel 2010.

☐ Graphical drawings were created using Microsoft Power Point 2010.

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