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Techno-Economics of Optimised Residential Heating under Power Sector Decarbonisation

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Submitted in partial fulfilment of the requirements
for the degree of Doctor of Philosophy

Declaration

I hereby declare that the content of this thesis is a product of my own work and other work is appropriately referenced.

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Abstract

The Climate Change Act constitutes legally binding legislation that requires the UK to reduce its greenhouse gas emissions by 80 per cent by 2050 relative to 1990. Decarbonising the electricity and heat sectors is fundamental to achieving this target. Since the challenge could potentially involve several million heating installations and several thousand megawatts of generation, there is a pressing need for tools that can provide insights into the impacts stemming from this transition.

Previous studies make use of coarse simplifications of links between the heat and electricity sectors. A primary contribution of this work is the linking of detailed models of electricity supply and residential heating. Analysis of future electricity price formation leads to questions regarding the financing of dispatch-able generation. Furthermore, these issues are seen to influence performance of residential heating systems.

In a low carbon future, fuel cell based micro cogeneration shows the most economic potential but is the worst performer in terms of emissions, and economic value can be eroded by low ramping limits and high minimum set points. Stirling engine based micro cogeneration is not economic in any of the scenarios considered due to low utilisation.

Although heat pumps produce the lowest emissions, investment does not yield economic gains unless they are incentivised to consume inexpensive excess low carbon generation. Resistive heaters are likely to be chosen over heat pumps in this setting since they are cheaper to install and produce significant economic benefits for consumers, though this could lead to significantly higher primary energy consumption with related environmental impacts.

Overall, this work has demonstrated that an important dynamic exists between electricity sector decarbonisation, market arrangements that drive electricity prices and technology choices in residential heating systems. Policy makers should be mindful of this dynamic when designing markets and policy instruments of the future.

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List of Symbols in the Dispatch Problem

SETS

J	Set of all generators in the dispatch problem $j \in J$
T	Set of all time periods for the dispatch problem $t \in T$

PARAMETERS

γ_s	Share of solar capacity that cannot be curtailed.
γ_w	Share of wind capacity that cannot be curtailed.
$\eta^p,\ \eta^g$	Efficiency of pumped storage in pumping (p) and generating (g) modes
$\phi_{j,0}^{on}$	On/off state indicator of unit j at the beginning of the planning horizon
A_j^f	Fuel cost for minimum operating point of unit j (£)
A_j^c	Fixed minimum carbon cost for minimum operating point of unit j (£)
D_t	Electricity demand in period t (MW)
F_j^c	Carbon cost for unit j (£/MWh)
F_j^f	Fuel cost for unit j (£/MWh)
L_j	Start-up cost for unit j (£)
$\underline{P_j}$	Minimum electricity generation for unit j if activated (MW)
$\overline{P_j}$	Generation capacity for unit j (MW)
$R_j^u,\ R_j^d$	Ramp-down limit between consecutive periods for unit j (MW)
R_t^{solar}	Total solar electricity generation in period t (MW)
R_j^u	Ramp-up limit between consecutive periods for unit j (MW)
R_t^{wind}	Total wind electricity generation in period t (MW)
T^{end}	Length of planning horizon in half hour periods (Half hours)
$U^p,\ U^g$	Maximum charge (p) and discharge (g) rate for pumped storage (MW)

BINARY VARIABLES

ϕ_t^g	Generating mode indicator for pumped storage in period t
$\phi_{j,t}^{on}$	On/off indicator for unit j in period t
ϕ_t^p	Pumping mode indicator for pumped storage in period t
$\phi_{j,t}^{sd}$	Shut down indicator for unit j in period t (true if unit shuts down in period t)
$\phi_{j,t}^{su}$	Start-up indicator for unit j in period t (true if unit starts up in period t)

CONTINUOUS VARIABLES

$c_{j,t}^{carbon}$	Carbon cost for unit j at period t (£)
$c_{j,t}^{CU}$	Capacity-utilisation cost for unit j in period t (£)
$c_{wind,t}^{CU}$	Capacity-utilisation cost for wind power in period t (£)
$c_{solar,t}^{CU}$	Capacity-utilisation cost for solar power in period t (£)
$c_{j,t}^{fuel}$	Fuel cost for unit j at period t (£)
$c_{j,t}^{O\&M}$	Operation and maintenance cost for unit j in period t (£)
$c_{j,t}^{startup}$	Start-up cost for unit j in period t (£)
e_t	Storage level of pumped storage in period t (MWh)
$p_{j,t}$	Electricity generated by unit j at period t (MW)
p_t^{solar}	Electricity injected from solar sources in period t (MW)
p_t^{wind}	Electricity injected from wind sources in period t (MW)
q_t	Electricity released or consumed by pumped storage in period t (MW)
q_t^p	Electricity consumed by pumped storage in pumping mode in period t (MW)
q_t^g	Electricity released by pumped storage in generating mode in period t (MW)

List of Symbols in the Heating System Problem

SETS

T	Set of all time periods $t \in T$
K	Set of all sample days $k \in K$

PARAMETERS

α_{gas}	Natural gas price (p/kWh)
α_{CO2}	Non-traded price of carbon (£/tonne)
α_t^{imp}	Retail price of electricity (p/kWh)
α_{SUC}	Cold start-up cost of micro co-generation unit (£)
α_{SUH}	Hot standby cost of micro co-generation (£)
$\alpha_t^{wholesale}$	Wholesale price of electricity (p/kWh)
δ_{mdt}	Minimum down time (five minute periods)
δ_{mut}	Minimum up time (five minute periods)
δ_{rmp}	Ramping limit (kW)
δ_{tdr}	Turn down ratio
η_B	Efficiency of natural gas boiler

η_{ch}	Charging efficiency of thermal energy storage
η_{disch}	Discharging efficiency of thermal energy storage
η_{el}	Electrical efficiency of CHP unit
η_{th}	Thermal efficiency of CHP unit
η_{EH}	Efficiency of resistive heater
E	Annual carbon emissions (kg)
Φ	Equivalent Annual Cost (£)
Ψ	Upfront cost of heating technology (£)
$\mathrm{A}^{wholesale}$	Mean value of wholesale price of electricity (p/kWh)
$\overline{B}$	Capacity of natural gas boiler (kW)
COP_{HP}	Coefficient of Performance of the heat pump
D_t	Electricity demand in the dispatch model in period t (MW)
D_t^{el}	Electricity demand in the heating system model (kW)
D_t^{th}	Thermal demand in the heating system model (kW)
e_{gas}	Carbon intensity of natural gas (kg/kWh)
e_{el}	Carbon intensity of electrical grid (kg/kWh)
$k_{wholesale}$	Ratio between wholesale price and retail price of electricity
L	Lifetime of heating technology (years)
$\overline{P^{el}}$	Electrical capacity of CHP unit (kW)
$\overline{P^{EH}}$	Capacity of resistive heater (kW)
$\overline{P^{HP}}$	Capacity of heat pump (kW)
r	Discount rate (%)
$\overline{S}$	Capacity of thermal energy storage (kWh)
T_{end}	End of the planning horizon for the heating system model
w_k	Weight of sample day k (Days)

BINARY VARIABLES

ϕ_t^+	Charging mode indicator for thermal energy storage
ϕ_t^-	Discharging mode indicator for thermal energy storage
ϕ_t^A	Active indicator for micro co-generation unit
ϕ_t^{SD}	Shut down indicator for micro co-generation unit
ϕ_t^{SU}	Start-up indicator for micro co-generation unit

CONTINUOUS VARIABLES

β_t	Operating cost of the heating system (£)
γ_t	Export revenue generated by the heating system (£)

λ	Objective function in the heating system (£)
Φ	Equivalent Annual Cost of heating technology (£)
B_t	Thermal output of the boiler in period t (kWh)
E	Annual carbon emissions (kg)
P_t^{exp}	Electricity exported by CHP unit in period t (kW)
P_t^{el}	Electricity generated by the CHP unit (kW)
P_t^{EH}	Electricity consumed by resistive heater in period t (kW)
$P_t{}^{HP}$	Electricity consumed by heat pump in period t (kW)
P_t^{imp}	Electricity imported in period t (kW)
P_t^{th}	Thermal output of CHP unit in period t (kW)
q_t	Electricity released or consumed by pumped storage in period t (MW)
R_t^{+}	Charging of thermal energy storage (kW)
R_t^{-}	Discharge from thermal energy storage (kW)
S_t	Storage level in the thermal energy storage (kWh)

List of Publications

The following publications have been produced as a result of work during this thesis:

Journal papers

Vijay, A., Fouquet, N., Staffell, I. and Hawkes, A., 2017. The value of electricity and reserve services in low carbon electricity systems. Applied Energy, 201, pp.111-123.

Vijay, A. and Hawkes, A., 2017. The techno-economics of small-scale residential heating in low carbon futures. Energies, 10(11), p.1915.

Vijay, A. and Hawkes, A., 2018. Impact of dynamic aspects on economics of fuel cell based micro co-generation in low carbon futures. Energy, 155, pp.874-886.

Vijay, A. and Hawkes, A., 2018. (submitted) Demand side flexibility from residential heating to absorb surplus renewables in low carbon futures. Renewable Energy.

Conference papers

Vijay, A., Fouquet, N., and Hawkes, A., 2015. Modelling the value of decentralised energy resources in supply-demand balancing for low carbon electricity systems. In 4th Int. Conf. Microgeneration Relat. Technol. (Microgen IV), Tokyo, Japan.

Acknowledgements

I owe my deepest gratitude to my supervisor Dr Adam Hawkes for his patience, support and encouragement. This thesis would not have been possible without his timely insights and guidance. Regular inputs from Dr Nicolas Fouquet and Dr Iain Staffell have also been very helpful during the course of my research. I would also like to express my gratitude to Airbus Group Innovations for providing financial support which enabled me to study at Imperial. Last, but by no means the least, I would like to thank my loved ones for their unyielding support and faith in my abilities. To them I dedicate this thesis.

1. Introduction

1.1. Research Motivation

Climate change is real and is a result of greenhouse gas emissions. Warming is resulting in retreating ice caps, increase in sea level and increase in surface temperatures. Human activity rather than natural fluctuations is the cause behind these effects. Concerted efforts are necessary to avoid irreversible consequences that will follow if left unchecked (IPCC, 2014). The mitigation of greenhouse gas emission is gaining importance due to a shift in focus towards long term ambitions by governments worldwide (United Nations, 2015).

The UK is a leading country in terms of energy policy in this regard. The 2008 Climate Change Act constitutes legally binding legislation that requires the UK to reduce its greenhouse gas emissions by 80 per cent by 2050 in comparison to 1990 (HM Government, 2008). The Climate Change Act also set up the Committee on Climate Change to advise the government on decisions and progress related to its targets. This committee established a series of carbon budgets to define the intermediate emission targets. The most recent Fifth carbon budget pertains to the period 2028-2032, and sets the target at 57 per cent below the levels seen in 1990 (Committee on Climate Change, 2015).

The power sector makes up nearly one-fourth of the total emissions in the UK (BEIS, 2017d). Targeting the power sector also has system wide benefits as it is closely linked to the industry, buildings and transport sectors. To achieve the 80 per cent goal, direct emissions from the power sector should be close to zero by 2050 (Committee on Climate Change, 2015). It is clear that a fundamental change in technology mix will be necessary for such a dramatic reduction.

One of the reasons for power sector decarbonisation being viewed as the cornerstone of energy system decarbonisation is the fact there are mature low carbon alternatives that can be introduced into the supply side of the system. Integration of such sources does not require intervention or behavioural changes from the consumer at least in the beginning. But there are long term implications of such a shift. As the uptake of decentralized low carbon sources gains prominence, the conventional view of unidirectional flow of power and energy from source to consumer will be upended. A low carbon future will involve increasing levels of consumers who interact with the utility by exporting electricity or changing their demand levels in response to changes in the supply side. The changes which will be encountered are not fully understood and existing tools used to operate the system are based on the conventional model of the electricity system which has not changed in the last two centuries. Hence, there is a pressing need for tools that can assess the effects of such fundamental shift in paradigms.

1.2. Research Questions

The main objective of this thesis can be summarised as:

> **Analyse how large scale uptake of low carbon generation in the power sector impacts economic and environmental performance of technologies in the residential heating sector.**

To this end, two systems are studied: generator operation in the supply side and domestic heating systems in the demand side. This thesis formulates four research questions to explore this topic:

> **Question 1:**
> **How does power sector decarbonisation affect generator operation and the commodity price of electricity?**

This question requires the analysis of increasing shares of low carbon generation in the overall energy mix. The main technology options considered are: renewables (mainly solar and wind), and nuclear. The intermittency in the case of renewables and inflexibility in the case of nuclear is likely to influence supply side operation and hence the commodity price of electricity.

> **Question 2:**
> **How does broader energy system decarbonisation affect the techno-economics of residential low carbon heating systems?**

This involves the replacement of existing technologies that serve thermal (natural gas boiler) and electrical (electricity imported from the central grid) demand. The baseline is compared with the inclusion of an electric heater, heat pump, micro cogeneration units and a hot water storage tank.

Question 3:
How does the incorporation of dynamic aspects affect the economics of fuel cell based micro cogeneration?

Improvements are made by adding possibly limiting constraints to the fuel cell in the form of start-up costs, ramping limits, minimum up/down time and turndown ratio. We evaluate the effects of these factors on economic viability.

Question 4:
How can residential heating aid in supply demand balancing of energy systems with high penetration of low carbon sources?

Since low carbon sources receive payments based on the amount of energy generated they generally refrain from turning down output. But this may be necessary in order to maintain system stability. In such cases the constraint payments are likely to be far in excess of the subsidies foregone by low carbon sources (Renewable Energy Foundation, 2011). Hence, a cost effective solution is necessary to ensure supply demand balance. This question explores how this service can be provided by residential heating systems.

There is a flow of logic in these questions. Question 1 introduces the low carbon future. Question 2 evaluates the viability of different residential heating technologies in response to the future scenario. Questions 3 and 4 tackle additional issues that are likely to be encountered in the future and analyse whether the results from Question 2 are subject to change in light of these new issues.

1.3. Research Methodology

This thesis develops a methodology that focuses on the evolution of two factors. Firstly, it takes a macro perspective by analysing the national level electricity grid. The impact of a transformation of the energy mix on the wholesale electricity price is quantified. Next, it takes a micro perspective by analysing an individual consumer in the form of a residential heating system. Different technologies are evaluated on the basis of economic viability and potential to support the electricity grid.

The critical assumption in this thesis is that residential heating systems have the ability to react to price signals sent by the system operator. The price of electricity is the main link between the supply side and the demand side. A time varying price is viewed as a mechanism to feed information back to the consumer about the status of the supply side. For example, a high electricity price implies that more expensive generators are coming online at which point distributed generation can support the grid by exporting electricity. Similarly, a low electricity price implies excess generation which can be consumed by flexible demand. In addition to reducing curtailment, this also allows the system operator to avoid expensive constraint payments to renewable sources participating in the balancing mechanism as explained later.

This work uses well known optimisation techniques to understand the economic operation of electricity grids and residential heating systems. A least cost optimisation model is used in both levels. At the electricity grid level, optimisation is required due to time varying demand, renewable output and non-linear characteristics of generator operation. Optimisation is required at the residential heating level due to time varying electricity prices and the presence of a thermal energy storage system.

The electricity price is derived from a unit commitment problem. Decisions regarding which generators are online and their respective output levels are determined by this optimisation problem. It is formulated as a Mixed Integer Linear Program. Transformation of the energy mix has an impact on the type of generators are dispatched and hence the cost of delivering electricity. Two electricity price regimes based on the Short Run Marginal Cost and the Long Run Marginal Cost of generation are considered.

In the residential heating system, the optimiser is aware of the variation in demand (electricity and heat) and electricity price. It calculates the strategy which minimizes the operating cost (which includes export revenue in case of micro cogeneration units). A technology is said to be economically viable when its Equivalent Annual Cost is lower than that of the baseline case involving a natural gas boiler and electricity from the central grid.

The initial assessment of fuel cell based micro cogeneration does not account for dynamic aspects of fuel cells. Since a plethora of subsystems need to be coordinated for smooth operation, dynamic aspects can affect performance. A new set of constraints are incorporated to account for factors such as minimum up time, minimum down time, turndown ratio, ramping limit and start-up cost.

The final question addressed by this work is related to excess electricity that is expensive to curtail. The solution proposed modifies the electricity price profile sent to residential heating systems. In order to change consumption patterns the system lowers the electricity price during periods of excess. These changes shift loads such that prohibitive constraint payments to low carbon sources can be avoided.

By answering these questions, this thesis tries to better understand the role that can be played by optimised residential heating in energy systems with high penetration of low carbon sources.

1.4. Thesis Outline

This thesis consists of eight chapters. The first two chapters serve as an introduction to the topic.

- Chapter 1 presents an overview of the research motivation, the questions addressed and a high level description of the methodology.
- Chapter 2 presents descriptions of the various technologies involved and a discussion of existing literature related to this thesis.

The chapters that follow are related to each of the research questions addressed. Chapter 3 and Chapter 4 serve as the foundation for the later sections.

- Chapter 3 is related to the impact of high penetration of low carbon sources on electricity prices.
- Chapter 4 analyses how the changes in electricity prices affect the economic and environmental performance of residential heating systems.

The subsequent chapters are extensions or alternate applications that build on the chapters mentioned above.

- Chapter 5 investigates whether dynamic aspects of fuel cell based micro cogeneration influence its economic performance.
- Chapter 6 examines the use of residential heating as a source of demand side flexibility in systems with high penetration of low carbon sources.

The final chapter, Chapter 7, presents a summary of the findings and possible directions of future work.

2. Background and Literature Review

2.1. Model Overview

This thesis combines two models to integrate the operation of two distinct systems. On one end of the spectrum we analyse the supply side with a national level energy system model. This power dispatch model simulates operation of generators in the electricity grid. On the other end of the spectrum, we analyse the operation of an optimised heating system of a residential consumer. As explained earlier, the electricity price profile is the sole link between the models as shown in Figure 1. Different variations of the two models described are used in the following chapters. Details about the overlaps and modifications are described below.

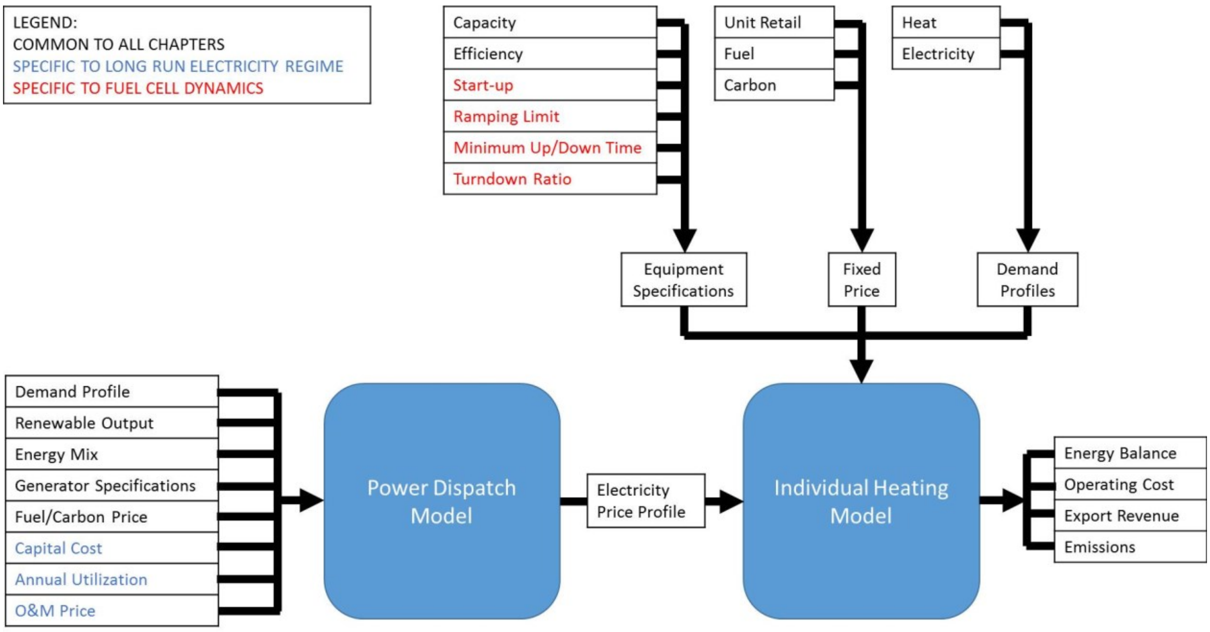

Figure 1 - Model overview

The foundation is laid by Chapter 3 which focuses on the power dispatch model in a future scenario. Here we assess the impact of a transformation of the energy mix on the wholesale price of electricity. This chapter makes use of the status quo in terms of electricity price regimes. The status quo makes use of the Short Run Marginal Cost to determine the wholesale price of electricity. This model makes use of several inputs such as demand profiles, renewable output profiles, energy mix, generator specifications, and fuel and carbon price. The main output under consideration is the electricity price.

Since the status quo based on the Short Run Marginal cost is found to be lacking in Chapter 3, we introduce an alternative electricity price regime based on Long Run Marginal Cost in Chapter 4. This requires the inclusion of three additional factors in the objective function: capital cost, annual utilisation and operation and maintenance cost of different technologies. All other equations from the short run regime are retained.

This electricity price profile is sent to the individual heating system model in Chapter 4. The energy balance is optimised according to the least cost operating strategy. Representation of heating components is restricted to capacity and efficiency. This is sufficient to assess the viability of the heating technologies in different electricity price regimes.

Chapter 5 improves upon Chapter 4 by accounting for dynamic aspects of fuel cells. Most of the equations from Chapter 4 are retained with the exception of operating costs. This is changed to account for start-up costs. New equations are added to represent the following dynamic parameters: start-up, ramping limit, minimum up time, minimum down time and turndown ratio.

The model used in Chapter 6 is the similar to the one used in Chapter 4. It makes use of the long run electricity price regime and a basic representation of the heating system. The main difference here is the modification of the electricity price profile. When there is excess electricity from low carbon sources, the retail price of electricity is lowered to zero. Operation of all other systems remains the same as seen in Chapter 4.

2.1.1. Existing Approaches to Modelling

This section will provide an introduction to the different alternatives available while modelling the two systems described above. Let us consider the national level electricity system model first. The main output required from this model is the electricity price. There are three main types of models which can achieve this result: agent based models, econometric models and bottom up models. Agent based models rely on simulating the activity of the different stakeholders involved to calculate the electricity price. This type of model is particularly useful when examining a system where some actors have a disproportionate amount of power to influence market outcomes. Hence by simulating each individual’s incentives and actions strategic behaviour can be modelled. But this intrinsic strength of agent based modelling is also a weakness. The model has to make use of mathematical assumptions regarding the stakeholders, their strategies, their incentives and their interactions with other agents. A large amount of uncertainty surrounds each one of these model assumptions. Since, very little is known about the incentives that will be available and the strategies that will be employed twenty years into the future, this approach was not adopted.

Another popular approach to predict electricity price is the use of econometrics. Econometric methods rely on large databases of historic data from the markets being modelled. They calculate future prices by regressing previous prices and other independent quantities related to demand, weather, temperature etc. The basic underlying assumption here is that future patterns will have a close resemblance to patterns encountered in the past. While this may be true for short term predictions, it loses significance when applied to long term scenarios.

Engineering economic approaches based on bottom up models alleviate this issue by making use of detailed descriptions of the technologies themselves. They do not rely on historic data. They leverage technical depth to describe scenarios in the future. They have the advantage of being able to incorporate advances in efficiency or emissions by changing the specifications used to model the equipment. Hence, this type of model is deemed to be the most appropriate for the purposes of this thesis. More detailed descriptions of individual references on this topic can be found in Section 2.3.

When considering the heating system model, it is common practice to consider load-following operation. Such models simply step through time and control the equipment based on the local load encountered in the system. An alternative to this is the design optimisation approach. Here, the system identifies a static operating point which minimises energy consumption or maximises efficiency. While these approaches may be convenient when fixed tariffs are encountered, they are extremely inefficient when a time varying real time electricity price is encountered. Another factor that works against such models is the presence of thermal energy storage which also requires strategic decision making.

Optimal operating models make use of mathematical programming to determine the operating strategy. Descriptions of the equipment, energy balance, efficiency and capacity are incorporated into the optimisation problem. Thus, these models can calculate operating strategies that exploit the variation of electricity prices to provide the most value to the consumer. Hence this approach has been adopted for the heating systems considered in this thesis. More detailed descriptions of individual references on this topic can be found in Section 2.3.

Up till now, this section has discussed variations in the problem definition itself. These classifications lead to the selection of optimal operation models. Both the national level electricity system and the individual heating system make use of an optimisation problem to calculate operating strategies. More specifically, they make use of Mixed Integer Linear Programs (MILPs). These problems are a subset of optimisation problems known as Linear Programs. Linear Programs are of the following form.

$$Minimise: c^T x \tag{1}$$

$$Subject\ to: Ax \leq b \tag{2}$$

$$And\ x \geq 0 \tag{3}$$

Where x is a vector of optimisation variables, c and b are vectors of known coefficients and A is a known matrix of coefficients. When some optimisation variables in x are constrained to integer or binary values, the problem is known as a Mixed Integer Linear Program. Now let us consider how these problems are solved.

Solving discrete problems is more difficult than solving continuous problems. This is not intuitive since continuous problems have an infinite number of solution possibilities while discrete problems have a finite number of possible outcomes. So by enumerating all of the discrete possibilities, the solution will become apparent. This is known as total enumeration and is feasible only when a small number of discrete variables are involved. As the number of discrete variables increases, the number of enumerations required increases exponentially.

Hence, solving discrete optimisation problems involves constructing a sequence of related, simpler problems, the solutions of which converges to the solution of the original problem. The most prominent solution method known as Branch and Bound which makes use of partial enumeration and relaxation techniques. Partial enumeration means that the strategy does not test out every possible combination but only a smaller portion of the solution space. And relaxation means that it allows some variables to take on continuous values. By using these two the Branch and Bound algorithm is able to search the space of unexplored solutions efficiently. The unexplored solution space is represented by a set of nodes in a dynamically generated search tree. The algorithm processes one node in each iteration which consists of three steps: selection of node to process, bound calculation and branching.

The root node or the starting node considers all discrete variables to be continuous. This provides a lower bound or the least possible objective function to the optimisation problem. Next steps are based on the decision variables which have fractional values. In the commonly used eager algorithm the first operation executed after selection is branching or subdivision of solution space into two or more candidates to be explored at a later point. The bounding function for each of these sub-spaces is compared to the current best solution. If all candidates of a subspace have a bounding value worse than the current best solution, it is discarded, else it is stored in the list of nodes to be explored. The Branch and Bound algorithm terminates when every node in the tree has been branched or terminated.

This thesis makes use of the CPLEX solver to handle MILPs. CPLEX uses the branch and cut algorithm. This also makes use of relaxations of the original problem. If the solution to the relaxed problem is integral the algorithm stops. If not, the algorithm adds a linear inequality constraint to the relaxed problem. This inequality constraint has to be satisfied by all the integer solutions but not the previous relaxed optimal solution. This process continues till the stopping criterion is satisfied.

2.1.2. Power Dispatch Problem

The power dispatch problem is a combination of unit commitment and economic dispatch. Unit commitment refers to the selection of generators which will be active during a particular time period and for how long. While they are active, the generators must meet the system load requirements at minimum operating cost. Economic dispatch involves the optimal allocation of load demand among the units which are active while satisfying their operating constraints.

Naturally the objective function of this optimisation problem consists of production and start-up costs. Production cost in this context refers to fuel and carbon costs. Conventionally, fuel cost is expressed as a quadratic function of generator output. This has been approximated as a linear function in this thesis.

$$f(p_{j,t}) = a_j p_{j,t} + b_j, \forall t \in T, \forall j \in J \tag{4}$$

Where $f(p_{j,t})$ is the fuel cost function, $p_{j,t}$ is the output of generator j at time t, and a_j and b_j are constants corresponding to generator j. Carbon cost has also been expressed as a linear function of generator output.

$$c(p_{j,t}) = e_j p_{j,t} + d_j, \forall t \in T, \forall j \in J \tag{5}$$

Where $c(p_{j,t})$ is the carbon cost function, $e_j$and d_j are corresponding constants for each generator. The next term in the objective function is the start-up cost. This term is included since units require a certain amount of energy to heat up the boiler or prepare the generator to be connected to the grid. It takes the following form.

$$s_{j,t} = L_j \phi_{j,t}, \forall t \in T, \forall j \in J \tag{6}$$

Where $s_{j,t}$ is the start-up cost function, L_j is the constant cost associated with each individual unit and $\phi_{j,t}$ is the binary indicator which is true if unit j started up in time interval t. This is based on integer constraints which describe start-up and shut down logic. In this thesis, the start-up cost varies according to the type of generator under consideration ranging from coal power plants which have high start-up costs to open cycle gas turbines which have low start-up costs.

The main system level constraint modelled in this thesis is the load balance constraint. This states that the sum of the output from all sources and discharge from storage must be equal to the sum of demand and charging actions associated with storage at all points of time. This constraint takes the following form.

$$\sum_{j\in J}(p_{j,t}) + p_t^{solar} + p_t^{wind} + q_t \ = D_t, \forall t \in T \tag{7}$$

Where p_t^{solar} and p_t^{wind} represent solar and wind output respectively. The terms q_t and D_t are associated with pumped storage and system demand. The feasible operating envelope is represented by the following constraints.

$$p_{j,t} \in \Pi_{j,t}, \forall t \in T, \forall j \in J \tag{8}$$

$$q_t \in \Gamma_t, \forall t \in T \tag{9}$$

Where $\Pi_{j,t}$ and Γ_t correspond to feasible operating envelopes for thermal and pumped storage units. These symbols represent a number of constraints which include limits on capacity and ramping. Capacity constraints describe the minimum and maximum limits on output of each generator. Renewable sources are modelled with a limit on curtailment. Ramping constraints correspond to the change in output between successive time intervals. This is particular relevant to nuclear power plants which are modelled with extremely limited ramping capacity. Finally, pumped storage is modelled via inter-temporal relations and limits on charging, discharging and storage capacity. Detailed equations related to each characteristic are explained later in Section 3.2.2.2. The reader is referred to Appendix C for a description of the different generating technologies considered in this thesis.

2.1.3. Residential Heating Problem

As seen in the previous section, the objective for the residential heating problem also involves minimising cost. This consists of three terms, cost associated with natural gas, cost associated with electricity and export revenue. Details of each technology type are presented in Section 0. For the purposes of this introduction we consider the micro cogeneration unit. Its objective function is as follows.

$$\text{Minimise} \sum_{t\in T}\left(\left(\frac{P_t^{th}}{\eta_{th}}+\frac{B_t}{\eta_B}\right)\left(\alpha_{gas}+\alpha_{CO2}e_{gas}\right)+P_t^{imp}\alpha_t^{imp}-P_t^{exp}\alpha_t^{wholesale}\right) \tag{10}$$

Where P_t^{th} is the thermal output of the micro cogeneration unit in period t, $\eta_{th}$is its thermal efficiency, B_t is the thermal output of the boiler in period t, η_B is the efficiency of the boiler, α_{gas} is the retail price of natural gas, α_{CO2} is the non-traded price of carbon, e_{gas} is the carbon intensity of natural gas, P_t^{imp} is the electricity imported in period t, α_t^{imp} is the price of importing electricity in period t, P_t^{exp} is the electricity exported in period t and finally, $\alpha_t^{wholesale}$ is the wholesale price of electricity in period t.

The electrical power balance equates generation to consumption from the view point of the consumer. It is formulated for the micro cogeneration unit as follows.

$$P_t^{imp}+P_t^{el}=P_t^{exp}+D_t^{el} \tag{11}$$

Where P_t^{el} is the electrical output of the micro cogeneration unit and D_t^{el} is the electrical demand at the house in period t. Thermal power balance relation does the same for thermal power as shown below.

$$B_t+P_t^{th}=D_t^{th}+R_t^{+}-R_t^{-} \tag{12}$$

Where D_t^{th} is the thermal demand at the house in period t, R_t^{+} is the discharge from thermal energy storage and R_t^{-} represents the charging of the thermal energy storage.

The other constraints are related to the feasible operating envelope of the components. This includes heat to power ratio, thermal storage operation, and capacity limits. Details of relations for each technology are presented in Section 0. The feasible operating envelope is modified in Chapter 5 to include dynamic characteristics of fuel cells. Details are presented in Section 5.3.4.

2.1.4. Implementation in Practice

Components other than the mathematical model are required for the system to function. The mathematical layer mentioned here can be considered as the Optimisation Layer in plant-wide control (Skogestad, 2004). This optimisation layer computes the set points required to minimise cost of operation and maximize revenue. The degrees of freedom calculated by this layer are then transferred to the next layer.

The next layer is known as the Regulatory Layer. The main function of this layer is disturbance rejection. It is responsible for maintaining the set-points specified by the optimisation layer and to make sure that the controlled variables do not drift away from their intended levels. This layer usually consists of low complexity single-input-single-output Proportional-Integral-Derivative (PID) controllers. Increasingly more complex Model Predictive Control (MPC) based components are also being used.

The same framework applies to the residential heating system studied in Chapter 4, Chapter 5 and Chapter 6. The set of manipulated variables does not change irrespective of whether dynamic aspects of fuel cells are considered or not. If the physical system had pronounced dynamic characteristics and the optimisation layer did not account for them, the gap between model and actual would be absorbed by the regulatory layer. For example, let us assume the optimisation layer increased the output of the micro cogeneration unit to rated capacity in a short period of time but the actual system takes longer to ramp up. In the interim the regulatory layer would simply hold the set-point at rated capacity until the physical system reaches the desired value. The advantage with including these characteristics in the optimisation layer makes sure that there is no unnecessary dissipation of energy due the discrepancy between the optimisation model and the real world.

Another factor that needs to be considered in practice is stability. Stability in control theory is the condition which states that the output of a linear system will stay bounded as long as the input remains bounded. This concept is meant to make sure that the regulatory controllers keep the system from straying into dangerous operating regions. Mathematically this requires the poles of the transfer function to have negative real values. Since there is a wealth of knowledge on regulatory controllers, this thesis assumes that they are a mature technology. Hence, this thesis assumes that as long as the set-points computed by the optimisation layer are within the safe operating envelope, which is guaranteed due to the constraints present in the model, the regulatory controllers will maintain the system in a stable state.

It can be argued that the optimisation layer can be replaced by other approaches such as reinforcement learning or fuzzy logic. Such approaches are better suited for systems whose characteristics are not known or are too complex to model mathematically. This is not the case with residential heating. The technologies in use are well understood and can be modelled accurately using optimisation problems. Another drawback is that reinforcement learning and fuzzy logic do not guarantee the lowest possible operating cost for the consumer. Hence, optimisation is the way forward chosen by this thesis.

2.2. Residential Heating

2.2.1. Situation in the UK

Residential heating is an integral part of energy consumption in the UK. The domestic sector accounted for nearly half the non-transport energy consumption in 2016 (BEIS, 2017b) as shown in Figure 2. Space heating is the dominant end use in the domestic sector making up nearly three quarters of the consumption (BEIS, 2017b).

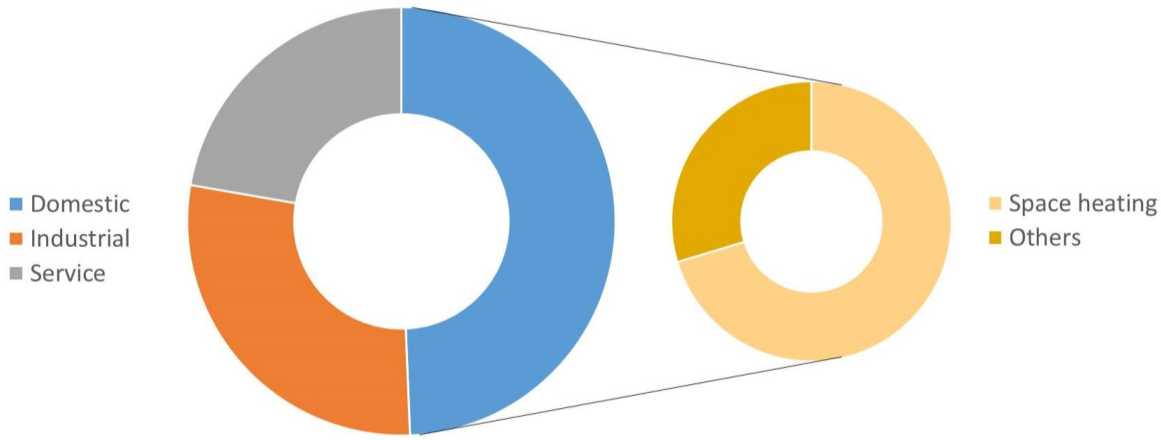

Figure 2 - Non-transport energy consumption in the UK in 2016. Data from (BEIS, 2017b).

Gas is the most common fuel used, accounting for 77 per cent of the space heating consumption followed by oil at 8 per cent, electricity at 7.6 per cent and bioenergy and waste at 5.3 per cent (BEIS, 2017b) as shown in Figure 3. Around 2 per cent of the overall consumption is from houses connected to district heating systems where heat is sold directly to the end customers.

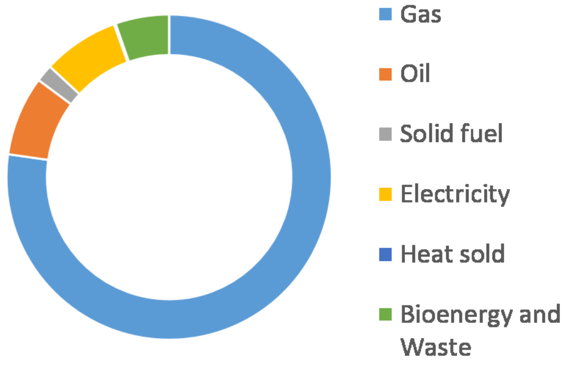

Figure 3 - Fuel used for space heating in the domestic sector in 2016. Data from (BEIS, 2017b).

This trend is also evidenced in the type of central heating found in dwellings in the UK. In the year 2012, nearly 87 per cent of all central heating installations were based on gas (BEIS, 2017b) as shown in Figure 4. Electricity was a distant second at 7 per cent, followed by oil at 4 per cent and solid fuels at 1 per cent. In contrast, the situation has changed dramatically since 1970, when nearly 68 per cent of the houses did not have a central heating facility. Advantages such as low capital and running cost make natural gas the heating technology of choice. The discovery of natural gas in the North Sea in the 1960s was also one of the factors leading to gas heating being installed in a large number of homes through the 1970s and 1980s.

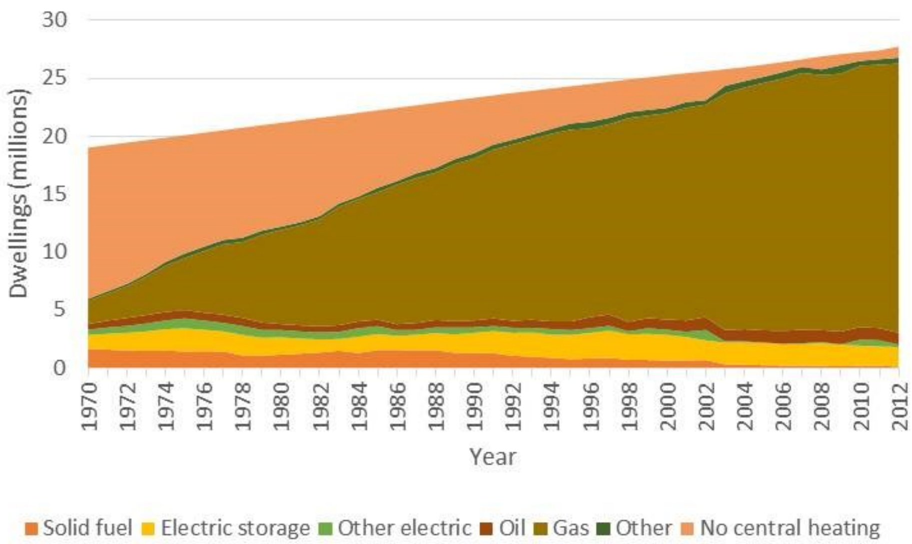

Figure 4 - Type of central heating found in dwellings in the UK. Data from (BEIS, 2017b).

This thesis explores the use of other technologies which either complement or replace the natural gas boiler in a low carbon future. The guiding principle used is that in order to be adopted the equivalent annual cost of new technology installed must be lower than that of the baseline involving the natural gas boiler. More details can be found in Chapter 3.

2.2.2. Natural Gas Boiler

Heating demand is primarily met through the use of natural gas boilers in the UK (Chaudry, Abeysekera, Hosseini, Jenkins, & Wu, 2015). This is due to ample supplies of natural gas, extensive natural gas transmission/distribution networks, low costs and relatively high efficiency.

A natural gas boiler is a controllable furnace with a continuous supply of fuel. It is an essential part of the heating system. Fuel is supplied from a natural gas pipeline that enters the house from the street. When switched on, a valve allows natural gas to enter a sealed combustion chamber inside the boiler through a series of jets. An electric burner ignites the fuel jet. The heat released is supplied to a heat exchanger carrying cold water. This heat exchanger carries the energy from the boiler to different parts of the house. It gives off heat through radiators and helps warm the room. Thus the temperature decreases and the resulting cold water is fed back to the boiler through the return circuit. An electric pump is used In order to keep the water circulation going.

Much like the gas turbine, the exhaust gases from a boiler are also at a significantly high temperature. In some cases, another heat exchanger is used to capture the heat from the exhaust gases that would otherwise be lost. Since the heat loss is reduced, efficiency is increased. This increase is of the order of 10 to 12 per cent. This concept which is similar to the combined cycle gas turbine discussed earlier is known as the condensing boiler. The name stems from the fact that after having lost heat, the steam in the exhaust condenses to water. This water is then drained out of the system.

Another type of boiler which is found in the market is known as the combination boiler. They are designed to provide both space heating and instantaneous hot water. This is done through separate pipes and heat exchangers for the two functions. It removes the need for a hot water tank. Thus households with space constraints choose combination boilers option over conventional boilers.

2.2.3. Heat Pump

The heat pump is a device that can deliver 3 kW of space heating with 1 kW of electricity input. While this might seem to defy the laws of thermodynamics, in reality it is not. The heat pump makes use of 1 kW of electricity to transfer 3 kW of heat from the outside to the inside.

Heat pumps make use of the same vapour compression cycles used in refrigerators and air-conditioners. The medium which transfers the heat is known as the refrigerant. The set up consists of four main components: a compressor, a condenser, a thermal expansion valve and evaporator. The refrigerant first enters the compressor as a gas where its pressure is increased. The increase in pressure also accompanied by an increase in temperature. Thus on the discharge side of the heat pump, the refrigerant is hot. This hot gas is cooled down to give a cold liquid through the use of a heat exchanger known as the condenser. This component is placed in the location where the heat is to be delivered. The cold liquid then passes through an expansion valve. Here the cold liquid is turned into an even colder gas. The cold gas then readily absorbs heat from the outside and is then sent back to the compressor and the process repeats itself. This has been illustrated in Figure 5.

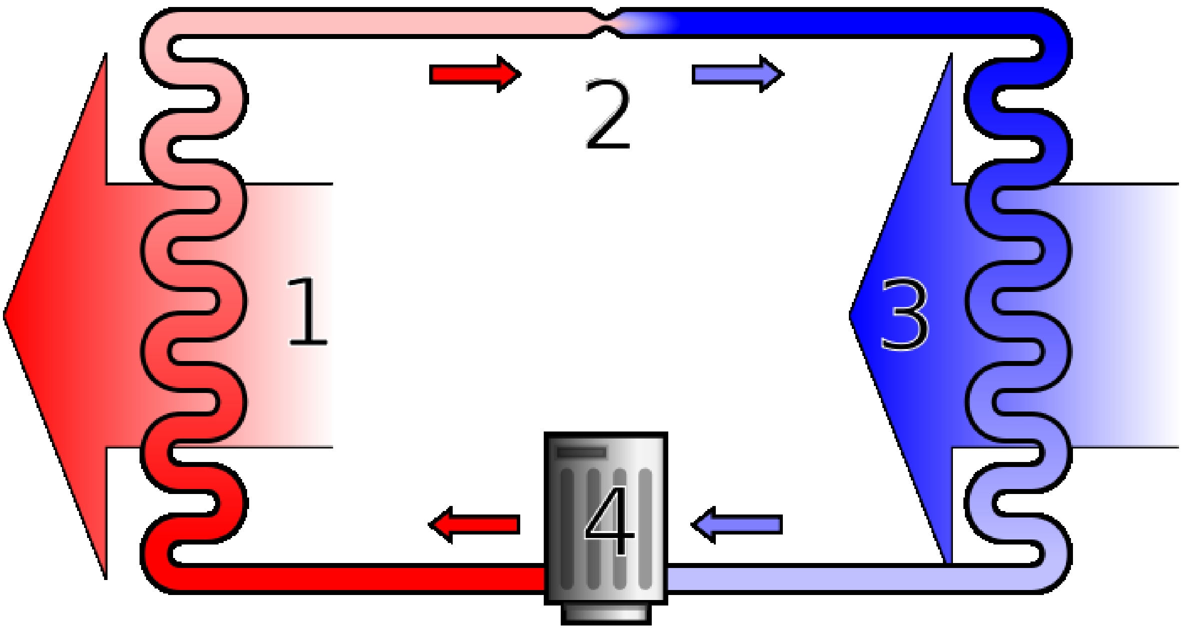

Figure 5 - Heat pump operation. Stages: 1) Condenser, 2) Expansion valve, 3) Evaporator, 4) Compressor. (Karonen, 2007)

Heat pumps can be divided into two types: air source heat pump and ground source heat pump. As the names suggest, the distinction is based on whether heat is absorbed from the air or the ground. Both types of heat pumps can be used to either heat or cool the inside of the house.

Operation of an air source heat pump consists of three cycles: the heating cycle, the cooling cycle and the defrost cycle. As described earlier, in the heating cycle heat is absorbed from the outside and released inside the house. The heating capacity of the heat pump is tied to the outdoor ambient temperature. If the outdoor temperature drops, the ability of the heat pump to transfer heat decreases as well. In the cooling cycle a reversing valve changes the direction of heat transfer. This is used during the summer when the heat pump absorbs heat from inside the house and releases it outside. While operating in heating mode, if the temperature outside falls below freezing point, the moisture being circulated through the outside coil will freeze over. This reduces the heat pump's ability to transfer heat. The amount of frost build up depends on the outdoor temperature and the moisture content in the air. This is monitored by measuring airflow, refrigerant pressure, temperature and pressure differentials between the inlet and outlet of the outdoor cool. If frost build up seriously hinders the heat pump's ability to function the defrost cycle has to be used. For a brief period the reversing valve switches such that heat is transferred to the outside.

Ground source heat pumps depend on a circuit of underground pipes outside the house. The refrigerant can be water or an antifreeze solution. The piping circuit can be an open or closed loop. Open loops make use of a water body such as a pond or a well. Here water from the water body is used as the heat exchange fluid. After it has been circulated through the system, water is returned ground. In a closed loop system antifreeze is circulated through a closed loop through pipes buried in the ground or water. The refrigerant absorbs heat from the antifreeze solution through a heat exchanger. The closed loop piping can be placed in a vertical configuration with U-bends if the household has space constraints. Some heat pumps make use of a direct exchange approach. Here copper tubes that are buried in the ground replace the heat exchanger. Soils that can be corrosive need to be avoided. The main advantages of using a ground source heat pump are higher coefficient of performance and higher energy savings. It also helps that ground source heat pumps do not require a defrost cycle as underground temperatures are much more stable than above ground temperature. Furthermore, since the heat pumps themselves are located inside the house, such problems are not encountered. The main disadvantage is the cost of the additional infrastructure that is needed in the form of the piping network.

Environmental performance of a heating system using heat pumps is tied to the emission factor of electricity from the central grid. Hence, they may not be beneficial in a scenario which allows fossil fuels to prevail. Other factors that need to be considered are the increase in electricity demand and the increased stress on the electric transmission and distribution network.

2.2.4. Micro Cogeneration

Micro cogeneration is merely a scaled down version of the well-established concept of large scale cogeneration. Cogeneration is a method to increase energy efficiency. Here the heat losses associated with power generation are captured and put to good use. A Sankey diagram that explains this concept is shown in Figure 6.

There are a plethora of advantages to using cogeneration: utilisation of waste heat, reduction of investment in upstream infrastructure, reduction in transmission and distribution losses and increase in reliability due to the presence of a back-up generator. Hence, we explore two possible technology options that could be useful in the future: Stirling engines and fuel cells.

2.2.4.1. Stirling Engine

A typical Stirling engines has two separate zones with different temperatures. The working fluid is shifted between these two zones to extract work. The main difference between a conventional engine and the Stirling engine is that the working fluid does not leave the engine at any point. The same fluid, usually air, is repeatedly used by all cycles in the engine.

The main advantage of using a micro cogeneration unit with a Stirling engine is that it can work with a variety of fuels. The heat driving the Stirling engine is transferred via heat exchangers to the working fluid and finally a heat sink. This heat can come from a variety of sources such as concentrated solar, geothermal, combustion of fuel and biomass. Since the heat source functions independently and its products do not come in contact with the internal parts of the engine, the Stirling engine can make use of fuels that other engines cannot. One such example is land fill gas.

Since the combustion products of land fill gas could deposit abrasive substances on conventional engines this is usually avoided. But in the case of a Stirling engine this is not an issue.

The main components are: hot/cold side heat exchangers, piston, displacer (if applicable), flywheel, and regenerator. The heat exchangers are used to maintain temperatures in the two zones of the Stirling engine. The two zones usually consist of cylinders. In small units the heat exchanger function may be served by the walls of the cylinders themselves. But large units require more heat to be transferred and hence larger surface areas area necessary. This can be achieved through internal or external fins or bore-hole tubes.

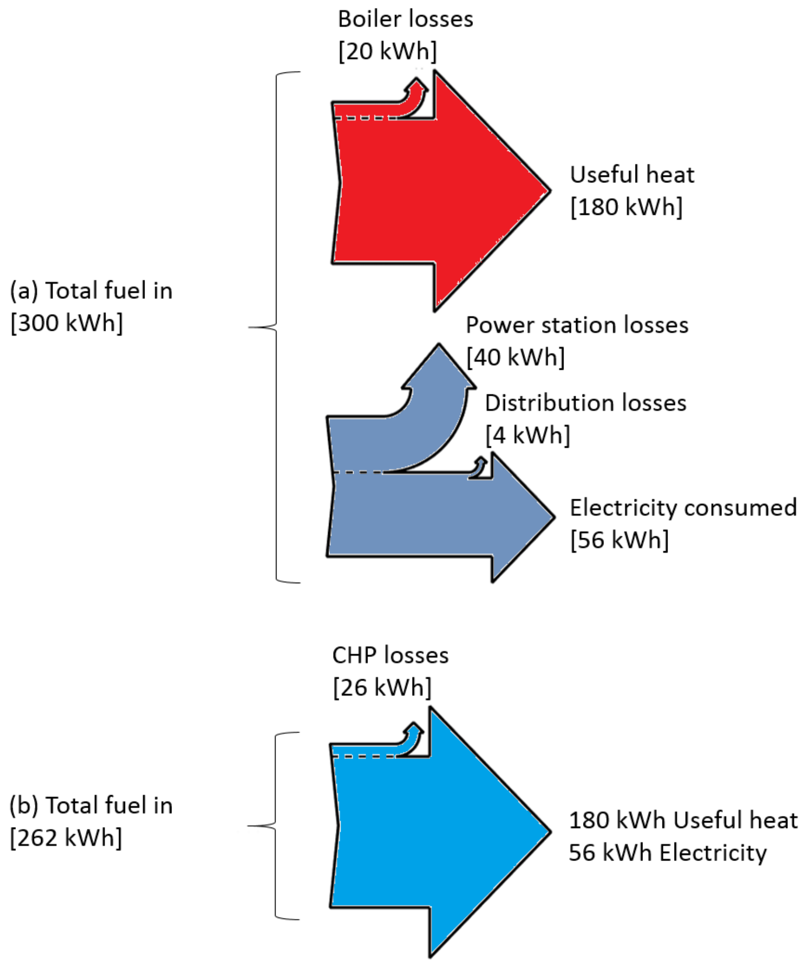

Figure 6 - Illustrative representation of the benefits of cogeneration (b) versus separate production (a)

The piston is a sliding member which is used to vary the volume available within the cylinders. It does this by moving from one extreme of the cylinder to the other. The work extracted from the Stirling engine is due to the gas pressure acting on the piston. The displacer is a special type of piston found in certain configurations of the Stirling engine. The clearance between the displacer and the cylinder walls is larger and hence this allows the working fluid to easily pass through the clearance. The piston and displacer are coupled to the flywheel. The flywheel is an inertial mass that reduces the fluctuations in engine speed and allows work to be extracted from the engine. This is done by coupling a suitable end use mechanism to the flywheel. And finally, the regenerator is an internal heat exchanger which allows the working fluid to be moved from one cylinder to another. The regenerator is used to capture the heat that would otherwise be dissipated into the environment. This in turn increases the efficiency of the Stirling engine. Typical regenerators consist of stacks of metal wire meshes.

There are three major Stirling engine configurations: alpha, beta and gamma. The main difference between them is the way in which the working fluid is moved between the hot and cold zones. The alpha configuration has two separate cylinders and pistons. The working fluid moves between the two through the regenerator. Both pistons are connected to the flywheel at the same point. The beta configuration consists of a single cylinder with hot and cold zones. The piston and displacer are connected to the flywheel with a specific phase difference. The beta and gamma Stirling engines carry similar moving parts, but the difference lies in the fact that the displacer is in a separate cylinder in the gamma Stirling engine. The differences between the configurations are evident in Figure 7.

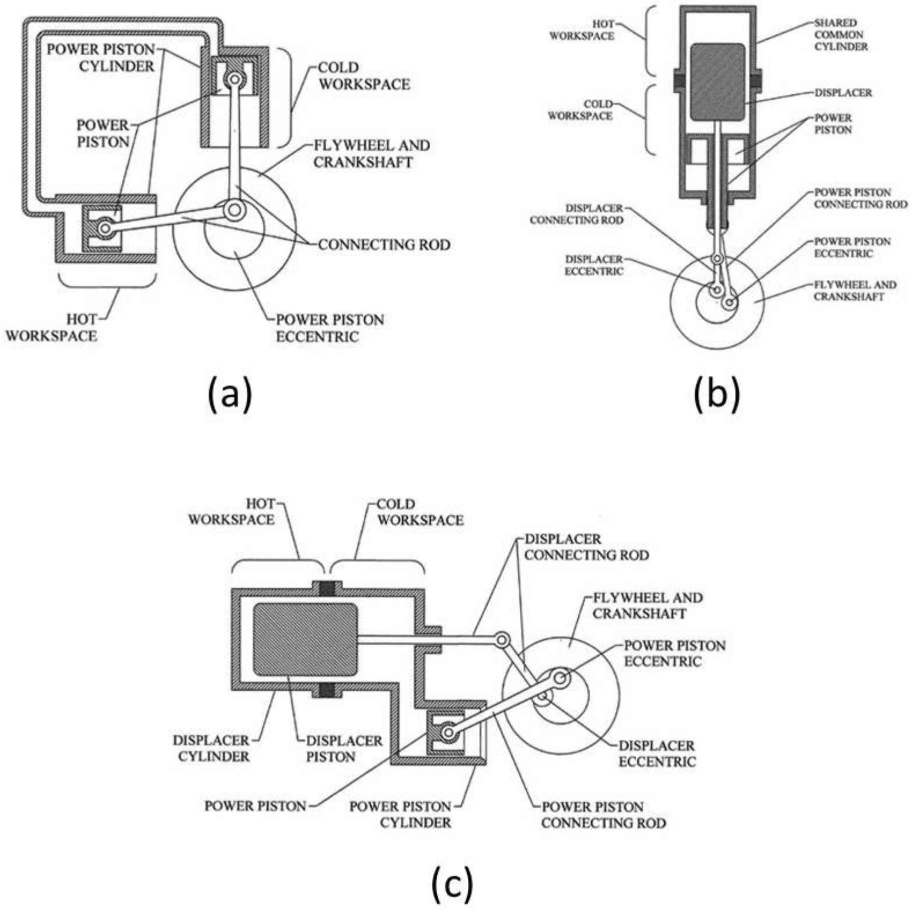

Figure 7 - Stirling engine configurations[1]: (a) Alpha (b) Beta and (c) Gamma (P. R. Foster, 2011)

1 Image credit: Phillip R. Foster, retrieved from https://scholar.lib.vt.edu/ejournals/JOTS/v37/v37n2/foster.html. Content licensed under CC BY 4.0.

2.2.4.2. Fuel Cell

Fuel cells are devices which convert the chemical energy found in fuel to electricity and heat without involving combustion. Its basic operation can be explained via its first demonstration by William R Grove who called it the Gaseous Voltaic Battery. The experimental setup that Grove introduced made use of two platinum electrodes which were half way submerged into a beaker of aqueous sulphuric acid. Separate tubes containing hydrogen and oxygen gas were inverted over the electrodes. The gas displaced the electrolyte when the tubes were lowered and an ammeter connected between the electrodes indicated a flow of electrons. It was observed that the flow of current waned after the initial deflection. But reaction rate and current could be returned to original levels by renewing the electrolyte. Hydrogen and oxygen were combining to form water an electric current was being produced.

Al-though the setup explains the concept well, it suffers from the drawback of low current magnitudes. This is in part due to the small contact area between the gas, the electrode and electrolyte. In this setup it is just a ring at the interface between the components mentioned. Another factor which affects current magnitude is the distance between the electrodes. As the electrolyte hinders movements of electrons, large distances translate to small currents. These two issues are tackled by making flat electrodes which provide a large surface area at the interface and thin electrolyte layers which reduce the distance between the electrodes. But another impeding factor that needs to be addressed is the reaction rate. As the reaction requires a certain amount of activation energy to be supplied before energy is released, other modifications are necessary.

Fuel cell technologies differ in the means adopted to tackle the issues related to reaction rate. Distinctions can also be made according to the materials they are made from, the fuels they make use of and the temperature ranges in which they operate. Of the technologies which are currently in use, low temperature Polymer Electrolyte Membrane Fuel Cells (PEMFC) and high temperature Solid Oxide Fuel Cells (SOFC) attract the most attention, research and development. Hence these are the two types discussed in this section.

Polymer Electrolyte Membrane Fuel Cells make use of catalysts to counter the problem of slow reaction rates. They can thus be operated at ambient temperature and can also be started quickly. This along with compact sizes makes them attractive for use in mobile and portable applications.

The anode-electrolyte-cathode is housed in a Membrane Electrode Assembly and several such cells are connected in series to make a fuel cell stack as shown in Figure 8.

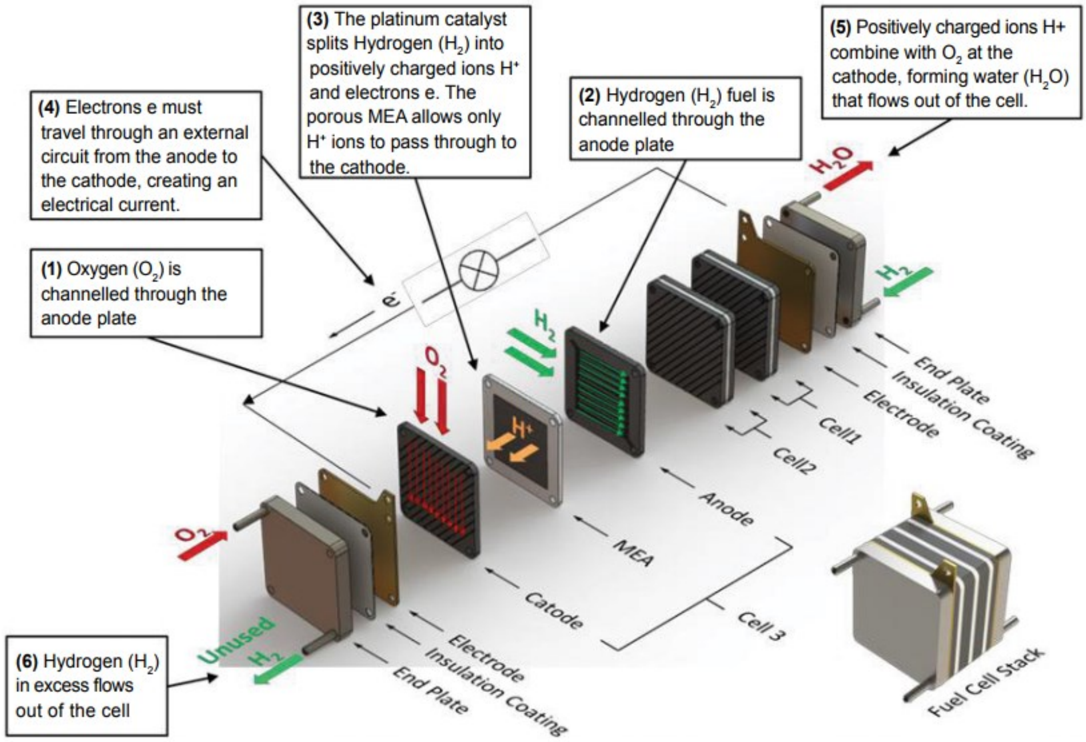

Figure 8 - Layout and operation of a typical Polymer Electrolyte Membrane Fuel Cell (Chen, Enearu, Montalvao, & Sutharssan, 2016)

The electrolyte used is an ion conduction polymer. As described in Figure 8, oxygen and hydrogen are channelled through the cathode and anode. Hydrogen gas is ionised using the platinum catalyst to H^+ ions or protons and electrons. The H^+ ions travel through the electrolyte and the electrons through the external circuit to reach the cathode. Here, they react with oxygen to create water.

In a Solid Oxide Fuel Cell, an oxide ion conducting ceramic material is used as the electrolyte. They are operated at high temperatures in excess of 800 degree Celsius. Hence, precious metal electro-catalysts are not required to increase reaction rates. Another advantage of using SOFCs is that fuels such as natural gas can be used directly or internally reformed. In such cases methane and carbon monoxide are used as fuel. This is done through the use the reforming and shifting reactions shown below.

$$CH_4 + H_2O \rightarrow CO + 3H_2 \text{ (Reforming)}$$

$$CO + H_2O \rightarrow CO_2 + H_2 \text{ (Shifting)}$$

The negatively charged O^{--} ions travel from the cathode through the electrolyte to react with the hydrogen to produce water and electrons. The electrons travel through the external circuit and current is produced.

The tubular design introduced by Siemens Westinghouse Power Corporation shown in Figure 9 is norm for practical SOFCs. The cathode, interconnector, electrolyte and anode are sequentially deposited on a tubular support material during production. Even though such designs require electrochemical vapour deposition methods that involve high fabrication costs, they are adopted since they eliminate the need for high temperature gas tight seals. This is done as follows. Each tube is sealed on one end. Air is fed through the centre of the tube and fuel is fed along the outside of the tube. Heat generated within the cell raises the temperature of the air to the fuel cell's operating temperature. The air flows through the tube and back up to the open top. Now, the air which is at a very high temperature and the unused fuel come in contact with each other resulting in instantaneous combustion. This serves as an additional heat source for the air supply. Since the tubular design has a built in air preheater and anode exhaust gas combustor, it does not require high temperature gas seals.

We have only discussed the fuel cell stack up till now. The fuel cell based micro cogeneration unit also contains other components which are related to balance-of-plant. These are auxiliary components required for the system to operate. These sub systems are discussed below.

Fuel processors are at the heart of fuel cell based micro cogeneration. This is because although hydrogen is the best fuel in terms of electrochemical performance, it is plagued by difficulties involving storage and lack of supply infrastructure. Natural gas is thus preferred due to its low cost, abundance and existing distribution infrastructure. Natural gas has to be converted to hydrogen containing low levels of sulphur and carbon monoxide for low temperature fuel cells. While PEMFCs require high purity hydrogen, SOFCs are capable of internal reforming. Natural gas can be converted to hydrogen using a variety of processes including steam reforming, partial oxidation and auto-thermal reforming.

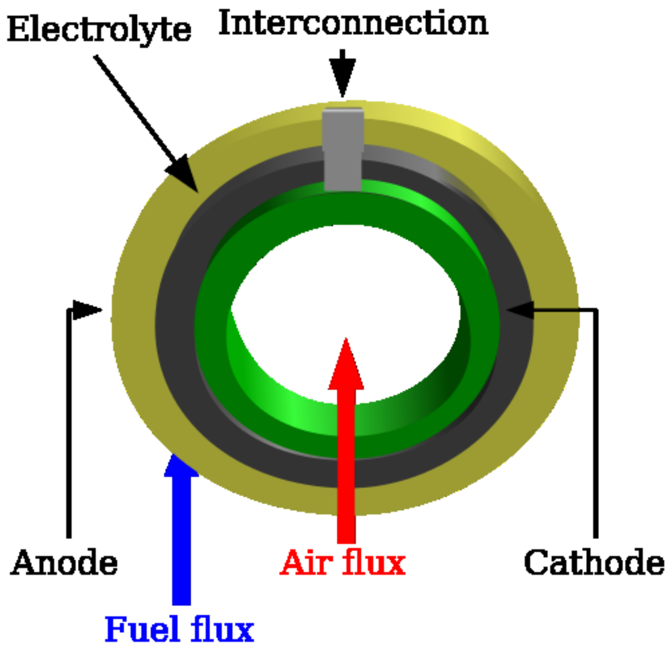

Figure 9 - Schematic of the cross section of tubular SOFCs[2] (Dschwen, 2013)

The products of the reforming stage will contain traces of carbon monoxide and sulphurous compounds. Both are poisonous to PEMFCs. While SOFCs can use carbon monoxide as fuel, they are still highly sensitive to sulphur. Therefore sulphur compounds are usually removed through reactions with ZnO or adsorption using activated carbon. As for carbon monoxide, it can be converted to carbon dioxide using as shift reactor. Other techniques such as selective oxidation of carbon monoxide and oxygen bleeding can be used, but they tend to increase system cost and decrease efficiency.

The DC output from a fuel cell is low in voltage and high in current. Before this can be used by appliances or exported back to the grid an electrical interface is necessary. This interface consists of an inverter and power conditioning systems.

Water management is important since it is needed for hydration of the electrolyte in PEMFCs and for steam reforming in SOFCs. This is usually removed from the heat exchanger condensers at the exit of the stack.

[2] Image credit: Dschwen, Grimlock. Retrieved from https://commons.wikimedia.org/wiki/File:SOFC-en.svg. Content licensed under CC BY-SA 3.0.

Heat management is also essential since it is tied to economic and environmental performance of the micro cogeneration unit. Useful heat is removed through the circulation of water or other fluids through the cooling plates in the stack for PEMFCs. Exit temperature is around 80 degree Celsius. Excess air is used to remove heat from SOFCs. Hence, air acts as both the reactant and the coolant in SOFCs. Heat recovery is more efficient in SOFCs since the exit temperature is much higher (of the order of hundreds of degree Celsius).

A reactant delivery system is also required. A blower is used for this purpose. This represents the largest parasitic load of the system. In SOFCs, the air has to be preheated to prevent thermal shock to the ceramic components in the stack. This is achieved through heat exchangers. Finally, control loops are needed for the various sensors and actuators that keep the system running.

2.3. Literature Review

2.3.1. Electricity Price Forecasting

Electricity markets are increasingly moving away from the vertically integrated utilities which acted as monopolies in the past (Rafal Weron, 2007). The unbundling of electricity markets has given rise to various stakeholders such as generators, suppliers and system operators. Electricity price is a crucial point of interest for these stakeholders since it is one of the most significant inputs to their decision making process. In the following sections we present an introduction to the main approaches currently used in electricity price forecasting.

2.3.1.1. Agent Based Models

The electricity market poses many aspects which are difficult to characterise such as asymmetric information, imperfect competition and strategic operations (Amman, Tesfatsion, Kendrick, Judd, & Rust, 1996). One way to address the complexity of this task is the usage of autonomous agents that define the activity of individual stakeholders. The amount of detail that can be described by these models has grown dramatically due to tremendous advances in computational resources. The agents in such models are goal oriented in the sense that they are tasked with maximizing an objective or utility. They can take decisions on their own and can learn over time about which actions work. They also have the ability to exchange information with other agents. Next, we discuss the notable models in literature.

EMCAS (Conzelmann, Boyd, Koritarov, & Veselka, 2005) is meant to be a tool that informs policy makers. It consists of several types of agents that represent generators, suppliers and transmission and distribution companies. It is able to determine electricity prices for every hour and location in the given system. Changes in market behaviour to various economic, financial and regulatory environments can be analysed. The heterogeneous nature of the model layers also allows the model to describe interactions which are driven by both technical and economic factors. Learning within agents happens by either observing previous strategies which performed well or by trying out new strategies and testing if they are worth pursuing.

N-ABLE (Ehlen & Scholand, 2005) is another tool meant to support public policy. The N-ABLE model is able to incorporate a range of economic sectors such as manufacturing, finance and households into the operation of the electricity market. It in addition to describing participants' buying and selling behaviour it also accounts for inventory capacities and long term planning actions. This model tries to address interdependencies between infrastructure and economic sectors and their vulnerabilities to disruption. It does this by making use of large scale Markov processes which allow interactions between the agents specified.

The objective of MAIS (Sueyoshi & Goto, 2010; Sueyoshi & Tadiparthi, 2008a, 2005, 2007, 2008b) is to estimate price variations in the US wholesale electricity market. This model contains agents with broad and limited learning capabilities. MAIS makes use of a mean reverting method which assumes that electricity prices eventually return to the historical average value of the series. The dynamics of power trading described in this model are not capable of predicting price spikes, this is an important direction that needs to be explored. Another direction that the authors highlight is the possibility of coexistence of agents with different learning algorithms.

The AMES (Li & Tesfatsion, 2009b, 2009a) test bed is an open source platform for agent based modelling of electricity systems. It has been developed in JAVA so that it is machine independent. It shares various characteristics with MASCEM (Praça, Ramos, Vale, & Cordeiro, 2003; Santos, Pinto, Praça, & Vale, 2016; Vale, Pinto, Praca, & Morais, 2011). Both simulate strategic bidding behaviour in electricity markets while incorporating transmission network constraints using optimal power flow. Both incorporate an independent operator responsible for market clearing. Finally, both incorporate reinforcement learning capabilities.

PowerACE (Bublitz, Ringler, Genoese, & Fichtner, 2014; Genoese, Sensfuß, Möst, & Rentz, 2007; Möst & Genoese, 2009; Sensfuß, Ragwitz, & Genoese, 2008) has been used to simulate electricity prices in Europe. It makes use of an equilibrium model to calculate prices. In contrast to optimal power flow, network congestion is handled by making use of a market coupling optimisation problem from (Meeus, Vandezande, Cole, & Belmans, 2009). PowerACE also incorporates long term capacity expansion planning. This is done by analysing the evolution of market prices and evaluating whether the net present value of investment is favourable.

2.3.1.2. Statistical Models

Several methods used to predict electricity prices are derived from existing statistical methods that are meant for load forecasting (Bunn, 2000). Such methods use historic time series data of electrical price or a combination of electrical price and exogenous factors to estimate future prices. The most important exogenous factors that contribute to electrical prices are historic and forecasted loads, time factors, fuel prices and weather data.

AutoRegressive Moving Average or ARMA models (Crespo Cuaresma, Hlouskova, Kossmeier, & Obersteiner, 2004; Jonsson, Pinson, Nielsen, Madsen, & Nielsen, 2013; Tan, Zhang, Wang, & Xu, 2010) make us of a linear combination of previous values of electricity price (AutoRegressive) and previous values of white noise (Moving Average) to determine the current value of electricity price. Auto Regressive Exogenous models (ARX) make use of exogenous inputs or external datasets in addition to the previous values of the predicted quantity as seen in (Kristiansen, 2012). Another variation includes a differencing step in order to handle non stationarity and is known as AutoRegressive Integrated Moving Average (ARIMA) method (Contreras, Espinola, Nogales, & Conejo, 2003). When the degree of differencing is allowed to take fractional values, it is known as AutoRegressive Fractional Integrated Moving Average (ARIFMA) as seen in (Ooms, Carnero, & Koopman, 2004).

ARMA variants assume homoscedasticity, in other words, they assume a constant variance and covariance function. Since electricity prices are characterised by heteroscedasticity or non-constant conditional variance, the ARCH or AutoRegressive Conditional Heteroscedastic was introduced (Engle, 1982). Here, the conditional variance is included through a weighted sum of squared preceding values. When the predicted value is dependent not only on the past value of the series but also the past values of conditional covariance they are known as Generalized AutoRegressive Conditional Heteroskedastic or GARCH models as seen in (Bollerslev, 1986). GARCH models are seen to perform well for electricity prices when combined with autoregression (H. Liu & Shi, 2013).

Electricity prices are known to have spikes. This implies that the representation of normal and high prices states should be different. This is handled through the use of regime switching models. One form of regime switching models is known as the Threshold AutoRegressive (TAR) model (H Tong & Lim, 1980; Howell Tong, 1978). Here different coefficients are associated with the previous values of electricity price when the value of an observable quantity is above a certain threshold. When the threshold variable chosen is a lagged value of the electricity price it is known as Self Exciting TAR (Ricky Rambharat, Brockwell, & Seppi, 2005). Other examples of regime switching models for electricity prices can be found in (Bierbrauer, Trück, & Weron, 2004; Karakatsani & Bunn, 2008; Paraschiv, Fleten, & Schürle, 2015).

2.3.1.3. Bottom-up Simulation Models

In contrast, engineering-economic bottom-up methods are rooted in the technical processes of electricity system operation. They make use of the connection between the demand level and the cost and operational features of the generators available. They are also known as production cost models since they involve least cost optimisation problems.

(Hummon et al., 2013) make use of two dispatch problems to determine reserve price. The opportunity cost of providing operating reserves in comparison to an "energy-only" dispatch is calculated. The price of reserves is based on the difference in market clearing price extracted from the PLEXOS model. This market clearing price is the dual value of the energy balance constraint. As dual values are not defined for integer valued constraints, this approach does not account for start-up or pumped storage discharge. This work improves upon the dual value approach through the use of a novel post processing algorithm which accounts for these missing factors.

Another example of a dispatch problem that makes use of the dual value approach can be found in (Grote, Maaz, Drees, & Moser, 2015). Results are driven by increase in primary energy and emission certificate prices. Apart from the price formation algorithm, there are several key differences in this comparison. We provide clear illustration of error values and validation with historical data. A longer time frame of twenty years is considered. And more diverse energy mix scenarios are considered.

(Weigt, 2009) and (Denny, O'Mahoney, & Lannoye, 2017) consider the merit order effect or the reduction in electricity price due to an increase in renewable capacity. Wind penetration is the primary factor under consideration. The main difference here is the fact that the current work studies the impact of an overall change in energy mix while both the references mentioned limit themselves to wind power.

Another variation of renewable impact analysis can be found in (Helistö, Kiviluoma, & Holttinen, 2017). As with the previous references they focus on the increase in renewable capacity. The distinction here is that this reference also includes generation expansion planning. Generation planning chooses the generation portfolio which minimises cost while ensuring security of supply. But (Helistö et al., 2017) does not consider a change in energy mix that prioritises climate change and meeting the two degree target. This thesis considers both a scenario in which the generation portfolio is tailored to meet environmental targets and a scenario which minimises cost while ensuring security of supply.

(Edmunds, Davies, Deane, & Pourkashanian, 2015) and (Schill, Pahle, & Gambardella, 2017) make use of a power dispatch model to analyse future scenarios where the energy mix changes. These references are very close to this work in terms of methodology, but do not focus on electricity prices. The focus is on thermal power plants. (Edmunds et al., 2015) study the change in operating regimes of thermal power plants and (Schill et al., 2017) study start-up costs in markets with high penetration of intermittent renewables.

Another variation of the term dispatch model is the use of a merit order stack. This involves arranging the generator in increasing order or marginal cost and simply choosing the least expensive set of generators that satisfy demand. Examples of this approach can be found in (Elliston, Diesendorf, & MacGill, 2012; Hirth, Ueckerdt, & Edenhofer, 2015).

2.3.1.4. Analysis and Way Forward

Although there seems to be a multitude of forecasting algorithms they can be grouped according to the types specified in this section. The first simulates individual actions to arrive at a collective behaviour and hence prices, the second makes use of historical patterns as a guide to predict future prices and the third which makes use of technology rich models to simulate electricity system operation in the future and hence derive the electricity price from this information. The main criteria that must be kept in mind is that this thesis considers long term prediction horizons nearly twenty years into the future and that a radical change in the energy mix is likely to be encountered in such a future. Hence the utility of each of these prediction methods must be evaluated according to its ability to satisfy these two requirements. The motivation behind the model choice made by this thesis becomes evident upon analysing the strengths and merits of each method as follows.

While agent based models are extremely flexible tools to describe strategic behaviour, they also have their weaknesses. Agent based systems are reliant on the rules and assumptions that govern the activities of the agents. Design choices involve making assumptions or abstractions of the stakeholders, their strategies, their interactions and the incentives. This involves a substantial amount of uncertainty. Variation in this internal structure may produce drastically different results. Another obstacle is that once the wheels are set in motion it is not straight forward to understand collective behaviour of agents. This issue is exacerbated by the possible presence of artefacts. Artefacts represent the gap between the assumptions that are actually causing the results to conform to validation data and what the developer thinks is leading to favourable results.

Statistical methods can only represent systems that have not undergone fundamental change. They rely on historical data to determine a function that matches the inputs to future prices. The relationships extracted are only valid if the future has similar properties to the past, and so are not suitable for long term price forecasts where radical system change is expected, as is the case with electricity system decarbonisation.

Bottom-up simulation models do not rely on the future being similar to the past. Engineering-economic models therefore are more appropriate in medium and long term scenario development. Long term studies require technical depth in order to model changes in the technologies and changes in the way that technologies interact. Such models have the advantage of being able to incorporate improvements in generation efficiency, reduction in emissions or other equipment specifications as parameters in a technology rich model. Hence bottom-up simulations models have been used in Chapter 3 of this thesis.

2.3.2. Low Carbon Residential Heating

2.3.2.1. Approaches to Heat Decarbonisation

Heat decarbonisation measures can be broadly classified into four groups: Behavioural and efficiency measures, electric heating, low carbon gases and district heating networks. Behavioural and efficiency measures can reduce demand through the use of insulation (Jelle, 2011), orientation (Laustsen, 2008), heating controls (J. Cockroft, Cowie, Samuel, & Strachan, 2017) high efficiency boilers (Labanca, Suerkemper, Bertoldi, Irrek, & Duplessis, 2015) and changes in behaviour or attitudes towards heating (Parkhill, Demski, Butler, Spence, & Pidgeon, 2013). Another approach to efficiency is the use of micro combined heat and power (micro-CHP) to produce both electricity and heat onsite (Murugan & Horák, 2016). Low carbon electricity is also a key contender, as the electricity grid begins to incorporate higher shares of wind, solar and other low carbon sources. Heat pumps present an opportunity to consume this electricity and reduce carbon emissions in the process (Carmo, Detlefsen, & Nielsen, 2014). Bioenergy can reduce GHG emissions by processing renewable materials such as wastewater into useful fuels, most commonly through anaerobic digestion (Weiland, 2010). Synthetic natural gas and hydrogen are other possible alternatives to natural gas (P. Dodds et al., 2015; Haro, Johnsson, & Thunman, 2016), and can be applied in conventional technologies such as boilers or alternatives such as fuel cell based micro-CHP. Furthermore, larger-scale heat production coupled with a heat distribution network, also offers opportunities to decarbonise heating at various levels ranging from community to city wide projects (Connolly et al., 2014).

Many studies consider specific options for the decarbonisation of heat. Combined heat and power, heat networks and fuel substitution are seen to be options that can potentially decrease carbon emissions in industry (BEIS, 2013b). A wide range of other options are also present in the literature: Energy efficiency is likely to be part of the future regardless of the end-use technology and supply source chosen, and hence clear goals must be set to encourage their adoption (Committee on Climate Change, 2016). Heat pumps are another option. Although entailing high capital cost, heat pumps are seen produce considerable emission savings (Jeremy Cockroft & Kelly, 2006), though this clearly depends on prevailing conditions such as the carbon intensity of the national electricity grid (Hanna, Parrish, & Gross, 2016). District heating is also seen to show great promise to reduce emissions but is highly dependent on policy or regulatory support in order to support coordinated roll out and uptake (S. Foster, Love, & Walker, 2015). Direct use of hydrogen is an option with the added benefit of possibly using existing gas network infrastructure, but would require network adaptation and consumers to switch appliances (P. E. Dodds & Demoullin, 2013). Thus, the challenge of decarbonising heat is far from solved. While many articles in the literature consider a single heating technology, relatively few are devoted to the comparison of different heating options. These are discussed below.

2.3.2.2. Comparisons of Heating Technologies in Existing Literature

(Peacock & Newborough, 2005) focus on the environmental aspects of residential cogeneration systems. A dwelling whose demand values were close to the nationwide average in the UK was chosen for investigation. Control is governed by a set of if then rules that decide when the unit is activated and what the output levels are. Operating strategies are seen to strongly influence carbon savings. Some strategies even result in higher emissions than the boiler baseline. An important aspect of the model is the restriction on the dumping of heat. In other words the heat generated cannot be greater than on-site demand in all cases. This factor affects the performance of Stirling engines due to their high heat to power ratio. Fuel cells fare better since they have higher utilisation rates. This is because they produce lesser heat in comparison to Stirling engines and they do not have to be turned off as frequently due to restrictions on heat dumping. This means that the savings from cogeneration of heat and electricity are more pronounced in the case of fuel cells.

Energy, environmental and economic factors are analysed by (Roselli, Sasso, Sibilio, & Tzscheutschler, 2011). Stirling engine and the internal combustion engine are the prime movers considered. Various commercially available cogeneration units have been used as part of an experimental study. This reveals nuances in the commercially available products that may not have been considered in a modelling study. For example, some models do not allow part load operation. They only support either an ON or OFF state. As expected, the economics are closely tied to the number of hours that the cogeneration unit operates in a year. The more the system operates at full load the better the financials. This factor has a stronger impact on the results than gas price and feed in tariff of electricity.

The maximum allowable cost of various cogeneration systems can also be used as an economic index as seen in (Barbieri, Spina, & Venturini, 2012). This study also includes a thermal storage tank. The results reveal that proper sizing of the thermal storage tank can greatly improve savings in primary energy consumption. It should be noted that all cogeneration units are operated in ON/OFF mode. No modulation of output is possible. This means that the unit is switched off if the output exceeds on-site demand and thermal storage capacity. In contrast to previous studies, the demand profile matched the heat to power ratio of the Stirling engine making it an attractive technology. This is also reflected in their recommendations related to prime mover sizing. As export revenue is not significant Barbieri et al. prefer to opt for a lower value of electrical output.

Heat pumps are compared with micro cogeneration units and boilers by (Pineau, Rivière, Stabat, Hoang, & Archambault, 2013). Distinctive feature of this study is that it accounts for the impact of electricity generation mix on the performance of the residential heating system. It assigns different values of emission factors for case studies in different countries. France with more nuclear capacity has a lower emission factor than Germany and Italy. This tilts the balance in favour of heat pumps and against micro cogeneration when electricity wins over natural gas in terms of emissions. But the results also reveal that heat pumps are at a disadvantage in terms of primary energy consumptions in cold climates. This is due to the fact that their Coefficient of Performance (CoP) is linked to the outdoor temperature. In cold climates their CoP decreases resulting in an increase in primary energy consumption.

Dynamic simulations of micro cogeneration systems are conducted by (Rosato, Sibilio, & Ciampi, 2013) to evaluate the performance of internal combustion engines and Stirling engines. The models used were developed within Annex 42 of the International Energy Agency's Energy Conservation in Buildings and Community Systems Programme (IEA/ECBCS). These models are able to account for transient behaviour, part load efficiency and system interactions. Rosato et al. state that irrespective of the prime mover technology used there is a clear improvement in terms of primary energy consumption, emissions and operating costs. Performance of lower heat to power internal combustion engines is better than the high heat to power Stirling engines. The use of a thermal storage tank is also considered in the simulations.

The importance of operating strategies while using heat pumps and fuel cell based micro cogeneration units was investigated by (Cooper, Hammond, McManus, Ramallo-Gonzlez, & Rogers, 2014). Lumped thermal capacitance models are employed to represent the building and heating systems. This approach was chosen as a trade-off between accuracy and complexity. The focus is not on the detailed simulation of components but rather the analysis of a wide range of control options for the heating systems. For the heat pump, three control strategies are analysed. Fixed temperature aims to maintain a constant temperature in the buffer tank. Variable temperature uses different temperature set points depending on outdoor temperature and proportional control varies heat input as a function of the difference between the set-point and the dwelling temperature. For the fuel cell the six control approaches are either variants of constant output or heat led operation. Heat pumps perform well under proportional control. Since this study prioritises environmental impact, it recommends operating the fuel cell at full output. This allows the fuel cell to displace grid electricity and result in lowest emissions.

(Jeremy Cockroft & Kelly, 2006) quantify the environmental benefit of introducing alternative heating systems in the domestic sector. The case study is based on the UK. Three types of dwelling are studied: an apartment, a terraced dwelling and a semi-detached dwelling. Technologies considered include micro cogeneration units driven by a fuel cell, internal combustion engine or Stirling engine and a heat pump. Another facet of this study examines the link between the emissions and the thermodynamic specifications, namely efficiency of the heating systems. Generation mixes for the year 2005 and the year 2020 are included in the study. This is done to show the effect of a transition away from coal and fossil fuel. The study concludes that heat pumps provide the greatest carbon saving among the options considered.

In a similar vein, (Dorer & Weber, 2009) also evaluate a comparable set of heating systems. The difference here is that Dorer and Weber also consider performance related to energy in addition to environmental factors. They also consider two generation mixes, one based on Europe and an alternative with combined cycle power plants. Dynamic models were calibrated using experimental data. All heating systems except the solid oxide fuel cell were operated in heat following mode. The solid oxide fuel cell was operated continuously. This was done due to concerns about start/stop actions reducing the lifespan of the fuel cell. Surplus electricity generated was subtracted from the overall electricity delivered to the house. The results showed that performance varied with the energy mix considered. Cogeneration units perform well under the European energy mix while heat pumps fared better in the combined cycle power plant energy mix. This can be attributed to the higher efficiency and lower emission factor of the latter.

And finally we also consider some national level models which include heating systems (H.-M. Henning & Palzer, 2014; R. Lund & Mathiesen, 2015). The focus of such studies is the analysis of a future scenario with significantly higher penetration of renewable sources. Such near 100% renewable scenarios can thrive on sector coupling or the conversion of one form of energy to another before it is consumed by the end use sector. Hence they cover the possibility of renewables being used in end use sectors other than just electricity. They also include the use of power to gas technologies as a form of storage. Henning and Palzer (H.-M. Henning & Palzer, 2014) restrict themselves to heat and electricity end use sectors. Lund and Mathiesen (R. Lund & Mathiesen, 2015) also consider other end sectors such as transport and industry. Biomass also features in both models. The results are meant to inform policy makers about technology development.

2.3.2.3. Analysis and Way Forward

It is important to recognise that the decarbonisation of heat will take place within broader energy system decarbonisation, a point that has not been comprehensively studied. We have shown in Chapter 3 that decarbonisation of the power sector leads to changes in electricity prices. Therefore, it is important to consider the economic performance of heating technologies within this changing energy landscape. Typically, such cross-system interactions are investigated via use of whole energy system models. For example, the intersection between broader energy systems and the supply of heat has been studied in (H.-M. Henning & Palzer, 2014; R. Lund & Mathiesen, 2015). These tools typically operate at the national, regional or global level, and as such are necessarily coarsely temporally and spatially-resolved (S Pfenninger, Hawkes, & Keirstead, 2014). Though they are suitable for macro-level analysis, the characteristics of individual entities are lost during aggregation, and more detailed highly-resolved and investor-centric models are needed to explore and test the potential solutions that they present. In this study we consider options that an individual consumer can choose to install without requiring changes in heat network infrastructure or in the supply side.

The references discussed in the previous section are summarised in Table 1. The main distinctions between them are related to whether a current or future energy system is considered, the types of models that define operation and the different technologies compared.

Table 1 - Comparisons of heating technologies in the existing literature[3]

Reference	Region	Scenario	System Description	BO	HP	FC	SE	ICE
(Peacock & Newborough, 2005)	UK	Current	Individual	y		y	y	
(Roselli et al., 2011)	Germany, Italy	Current	Individual	y			y	y
(Barbieri, Spina, et al., 2012)	Italy	Current	Individual				y	y
(Pineau et al., 2013)	France, Germany, Italy, Netherlands	Current	Individual	y	y		y	
(Rosato et al., 2013)	Italy	Current	Individual	y			y	y
(Cooper et al., 2014)	UK	Current	Individual	y	y	y		
(Jeremy Cockroft & Kelly, 2006)	UK	Future	Individual	y	y	y	y	y
(Dorer & Weber, 2009)	Generic	Future	Individual	y	y	y	y	y
(H.-M. Henning & Palzer, 2014)	Germany	Future	Aggregated	y	y	y	y	y
(R. Lund & Mathiesen, 2015)	Denmark	Future	Aggregated	y	y	Other large CHP		

[3]Abbreviations: BO – Natural gas boiler, HP – Heat pump, FC – Fuel cell based cogeneration, SE – Stirling engine based cogeneration, ICE – Internal combustion engine based cogeneration.

References that compare individual heating systems are limited to the present-day energy system (Barbieri, Spina, et al., 2012; Cooper et al., 2014; Peacock & Newborough, 2005; Pineau et al., 2013; Rosato et al., 2013; Roselli et al., 2011), with the exception of (Jeremy Cockroft & Kelly, 2006; Dorer & Weber, 2009) where the discussion of the future is limited to the change in carbon intensity of electricity generation. Aggregated representations (H.-M. Henning & Palzer, 2014; R. Lund & Mathiesen, 2015) do not provide information about the performance of an individual household. Therefore, such models cannot showcase the impact of technology adoption on the individual consumer. Although many options exist, there exists no comparison between technologies with the status quo in terms of investment and operating cost in a future scenario. This is the focus of Chapter 4 of this thesis.

2.3.3. Fuel Cell Based Micro Cogeneration

Previous work that has been done on the modelling of fuel cell based micro co-generation can be broadly classified as simulation and optimisation based models. Optimisation can be further divided into engineering design optimisation and optimal operation based models.

2.3.3.1. Simulation Based Models

In simulation based approaches emphasis is laid on modelling responses to parameters that undergo change, for example, power or heat demand, temperature variations within a building, rate of heat exchange etc. The model steps through time and simulates how the components react to the changes in circumstances. The operating strategies are predefined and only serve as inputs to the model. Many variants exist, some make use of a constant output strategy: at maximum capacity (Alanne, Saari, Ugursal, & Good, 2006) or with the addition of ON/OFF logic (Bianchi, De Pascale, & Melino, 2013). Others make the micro co-generation unit follow electric or thermal demand (Hong, Kim, Koo, & Kim, 2014; Staffell, Green, & Kendall, 2008). Another simple strategy is to use different constant outputs tailored to different segments during the day (Napoli, Gandiglio, Lanzini, & Santarelli, 2015; Pellegrino, Lanzini, & Leone, 2015). The main purpose of such models is the off-design evaluation of the technology. In such models, demand profiles are input parameters. Depending on the type of operating strategy selected the energy consumption and hence the emissions can be calculated using subroutines that perform arithmetic operations. Economics are compared by using the same data to calculate the cost of fuel consumption and electricity import and the revenue generated from electricity export.

Another group of models calculate demand profiles from external parameters such as climatic conditions, building materials, building designs and occupancy patterns. In case the fuel cell micro cogeneration unit is operated in load following mode, equipment specifications are necessary for part load efficiencies. Otherwise, these building simulation models can be executed independently and their results are used to inform the techno-economic evaluations mentioned above. Thermal interactions can be modelled by using lumped thermal capacitances (Cooper et al., 2014), or commercial building simulations packages such as eQUEST (Naimaster & Sleiti, 2013), DesignBuilder (Elmer, Worall, Wu, & Riffat, 2015) or TRNSYS (Kazempoor, Dorer, & Weber, 2011). Sophisticated models describing the physics, chemistry and electrochemistry also exist (Nanaeda, Mueller, Brouwer, & Samuelsen, 2010).

2.3.3.2. Design Optimisation

The next category of fuel cell models revolves around choosing design parameters or operating conditions which minimise energy consumption or maximize efficiency. This usually involves the selection of a static operating point that is conducive for efficient long term operation. Naturally it follows that all the components of the fuel cell micro cogeneration unit need to be described in such models. This means that detailed models of the balance of plant are also necessary. Components described can include the fuel processor, shift reactor, reformer, blower, pre-heater, heat exchangers and burner.

(Gandiglio, Lanzini, Santarelli, & Leone, 2014) make use of a method known as pinch analysis for design optimisation. Pinch analysis is commonly used to optimise heat exchanger networks for a plant or process. This involves accounting for hot/cold streams and heat sources. The pinch point method specifies parameters such as the ideal temperature settings and network configurations for the micro cogeneration unit. (Xie, Wang, Jin, & Zhang, 2012) make use of energy exergy balances to support their analysis. Analysis separates useful streams such as electricity and hot water from streams that are not useful such as flue gases and condensate from the water separator. A process flow simulator is used to support the analysis. The effects of system parameters such as steam to carbon ratio, air to carbon ratio, hydrogen utilisation efficiency on system performance are also evaluated. (Barelli, Bidini, Gallorini, & Ottaviano, 2011a) analyse a similar concept based on energy-exergy analysis and process flow simulators. It involves the soft linking of electrochemical phenomena represented in FORTRAN with the process flow phenomena in AspenPlus (Barelli, Bidini, Gallorini, & Ottaviano, 2011b). This is done since AspenPlus does not support electrochemical reactions. Modelling the polarization curve which is a result of the electrochemical portion of the model is of utmost importance while calculating the output power from the micro cogeneration unit. Design analysis can also differ in the type of models involved. The simplest methods use zero-dimensional models (Barelli et al., 2011a) with black box representations where the focus is on mapping input and output quantities. When geometry is to be taken into account, one-dimensional (Haghighat Mamaghani, Najafi, Casalegno, & Rinaldi, 2017) and two-dimensional (Xu, Dang, & Bai, 2013) models are used.

Fuel cell models can also be combined with evolutionary programming to determine optimal operating points (Arsalis, Nielsen, & Kær, 2012). Here empirical relations from experimental data are used to represent the equipment in some of the cases. This allows for a large number of model runs which are necessary to prevent the algorithm from settling for local maxima instead of the global maximum.

2.3.3.3. Optimal Operation Models

This approach involves the calculation of the best possible operating strategies through the use of optimisation solvers. This is different from the previous approach which does not allow the set point to deviate from an optimal design point. In general, such models consist of an objective which minimises cost, energy or emissions and constraints on capacity and feasible operating envelope of the equipment.

The work of (Wakui, Wada, & Yokoyama, 2014) focuses on the situation in Japan and hence has been influenced by the prevailing policy conditions. The export of electricity back to the grid is not allowed in this country. Hence, micro cogeneration systems had to find alternative solutions to handle surplus electricity. One approach is to use the battery storage in plug-in hybrid electric vehicles (Wakui et al., 2014). This reference also evaluates the possibility of switching the cogeneration unit ON/OFF once a day. Such start-stop operation is enabled since the local demand is very low during the night. It is worth noting that it incorporates both electrical and thermal storage. This allows the system to decouple supply from demand in both electrical and thermal domains. This configuration along with an optimal operating strategy is seen to provide significant energy savings.

A subsequent reference by the same authors, (Aki, Wakui, & Yokoyama, 2016), deals with a modification of the problem described above. The authors tackle the no-electricity-export rule by grouping together households. This model allows the exchange of electricity and hot water between dwellings. By doing this the model can capitalise on complementary demand profiles. The energy management system consists of three layers: prediction, optimisation and real time operation. Prediction of supply and demand values happens a day in advance, optimisation happens every hour based on these predictions and real time operation tracks system variables continuously. A receding horizon control approach is employed. Here, the planning horizon is always extended for a specific number of time steps ahead of the current time period. Hence, by continuously revising the operating strategy, the model is able to mitigate risks associated with uncertainties in the prediction layer.

Environmental factors take centre stage in the work by (Adam, Fraga, & Brett, 2013). The optimisation problem aims to minimise the emissions in contrast to costs. A Mixed Integer Linear Program has been formulated to represent the fuel cell micro cogeneration unit, boiler and thermal storage tank. This model also calculates the optimal size of these components as well. The results indicate that the fuel cell micro cogeneration unit is better suited for houses whose electrical demand was comparable to thermal demand. This is a consequence of the heat to power ratio of the fuel cell which is close to unity.

The origins of the model described in this thesis can be traced back to the work of (Hawkes et al., 2006, 2007; Hawkes & Leach, 2005). This thesis adapts many features from these references: the comparison with a baseline involving boiler and grid electricity, the minimisation of energy cost and the use of Equivalent Annual Cost as a measure of economics. These references have made use of non-linear programming mathematics for fuel cell based micro co-generation units. Since such nonlinear problems were not suited to capturing parameters such as start-up, minimum up time and minimum down time, an improved Mixed Integer Linear Program (MILP) formulation was used in (Hawkes, Brett, & Brandon, 2009). The model described in this thesis adapts a similar formulation to the context of a low carbon future scenario with high penetration of solar, wind and nuclear sources. Details can be found in Chapter 5.

2.3.3.4. Analysis and Way Forward

Selection of modelling approach is determined by the objective of the study. Chapter 5 incorporates dynamic aspects of fuel cells into the operation of the micro cogeneration system in a low carbon future. It aims to evaluate two factors: firstly whether such dynamic aspects have an impact on the economics of such systems and secondly to identify which aspects of design impact the economics the most. Hence, it provides recommendations regarding aspects of product design that should be prioritised in the future. With this is mind, let us assess the approaches mentioned.

The main drawback of simulation based models is inefficiency. This is so because it does not involve strategic planning. Merely following the load can lead to problems while incorporating dynamic characteristics. The unit could be sensitive to load fluctuations and switch on the fuel cell for a brief blip in demand but be forced to remain active in the following periods which have no demand due to minimum up time specifications. In a similar fashion, the model could shut the unit down because the current period has no demand but be forced to remain inactive due to minimum down time specifications and thus miss out on energy savings when demand increases. Since they do not consider operation beyond just the current period, they cannot describe the operation of thermal energy storage units either.

It can be argued that the constant output capacity can be designed such that it serves the base load or minimum load that the system serves at all points of time. While this may be true for large heat networks and community based cogeneration units, residential household demand can dip to zero and remain there for sustained periods of time. During this time the micro cogeneration unit is dumping heat, wasting fuel. It is also losing a significant amount of money if the electricity export tariff is not large enough to improve economics.

Another limitation is that they are better suited for well-developed and mature technologies whose characteristics are already well known. As fuel cells are still considered to be an emerging technology, we need tools that can assess the best way to design and operate a future system rather than a more detailed analysis of existing configurations.

Design optimisation focuses on the variation of operating parameters to select a static set-point. Such set points are meant to be conducive for efficient long term operation without interruption. As mentioned earlier, the demand profiles encountered in a residential household do not have a minimum base load value. Hence, the static operation is likely to lead to inefficient operation.

Another limitation is that they provide very little information on the gaps in existing technology. This thesis deals with the change in performance in scenarios where the design parameters themselves are subject to change. Design optimisation is rooted in technology rich descriptions of current units and does not provide room for changes that could be encountered in the future.

The optimal operation model is capable of quantifying the change in key techno-economic criteria with respect to parameters which represent the dynamic characteristics of fuel cells. A sensitivity analysis of such models has the potential to identify design parameters that are likely to have a large impact on the energy and emission savings.

Having said this, making use of the nonlinear and quadratic programming models used in Hawkes et al. (Hawkes et al., 2006, 2007; Hawkes & Leach, 2005) does not allow us to incorporate dynamic characteristics easily since they do not support binary variables. The description of important dynamic parameters such as start-up, minimum up time and down time requires the problem to incorporate binary variables.

In comparison the Mixed Integer Linear Program from another reference by the same author (Hawkes, Brett, et al., 2009) is more suitable for the application considered in this thesis. Although, it cannot be used as is since it is meant for analysis of fuel cells in the context of a present day energy system. In order to analyse a low carbon future two additions are necessary: a time varying electricity price and a power dispatch model which can calculate this price given the radical change in energy mix. Hence, these modifications have been included in Chapter 5. This model offers sufficient detail and computational tractability to generate practical insights into the parameters that need to be prioritized during product design. Hence, this approach has been used in this thesis.

2.3.4. Absorbing Surplus Renewables via Residential Heating

2.3.4.1. Excess Renewable Production

Surplus generation in an energy system has been studied by (H. Lund & Münster, 2003). Power injected by wind and combined heat are decided by factors other than the variations in demand. This issue is of prime interest due to two reasons: wind and cogeneration account for more than half of the electricity production in the energy system considered, and surplus production threatens the very stability of the electricity grid. The energy system model used to analyse this problem takes a national level or macro perspective. This means that the different sectors are aggregated into single entities. Another feature of the model is that it is meant to plan energy investment strategies. Three measures are suggested, the curtailment of wind generation, curtailment of cogeneration units and replacement of boilers with heat pumps. The first two measures avoid surplus production and the final one introduces flexibility to absorb the surplus. The results reveal that the cost of avoiding surplus is lesser than investing in high voltage transmission lines and that investing in flexibility reduces surplus production.

(Pensini, Rasmussen, & Kempton, 2014) study whether excess renewable generation can displace fossil fuels used to supply heat. A hundred per cent renewable scenario has been considered. The authors argue that using excess electricity to supply heat is more cost effective than investing in large scale electrical storage. This is done either through the use of heat pumps or resistive heating. Heat pumps are part of a district heating system that also includes thermal energy storage in the form of hot water tanks. Resistive heating systems along with high temperature storage units are present in the individual households. The excess electricity is distributed among the houses in this case and conversion takes place locally. In each case a natural gas boiler is installed for backup. The results indicate that heat pumps with central storage perform better in most cases except when zero cost electricity is available. Resistive heaters perform better in this case.

The excess electricity profile in (Pensini et al., 2014) was generated from a different model by (Budischak et al., 2013). The focus of this study was to analyse whether large penetrations of renewables and storage can satisfy demand for a given fraction of hours. As the greatest values of excess electricity was observed to occur in winter, the authors chose to analyse the supply of heat. This was done offline after the cost optimum of renewable investment was determined. It was seen that there a great match between the excess generation and demand for heat between November and May. Although this match is based on monthly aggregated values, it is an encouraging prospect that requires further research.

2.3.4.2. Optimisation of Demand Response from Residential Heating

The work of (Papaefthymiou, Hasche, & Nabe, 2012) investigates how heat pumps can help integrate wind power through demand side flexibility. It makes use of passive storage within the building. Thus the temperature profile decides maximum available storage capacity at any point of time. This information generated from a building stock model which then relays it to a unit commitment model. The unit commitment model determines market prices, plant dispatch and the income of power plants. Thus this reference integrates the thermal model of the building stock with a high level electricity market model. Future scenarios for the German energy system in the year 2020 and 2030 are considered. Demand response actions are deviations from the business-as-usual heat driven operating strategy. The results indicate that demand side management is a viable alternative to conventional storage to help integrate wind power.

(Hedegaard & Balyk, 2013) propose an approach to incorporate heating system operation into energy system models. The case study considered is the Danish energy system in the year 2030. Heat pumps and thermal storage tanks are used as instruments of demand side management. The energy system model optimises investment in generation, storage and transmission capacities and operation of the overall system. The buildings are assumed to make use of a constant temperature setting. Hence heating profiles can be generated for this temperature setting. However, the inclusion of demand side management allows the temperature to vary within a tolerance band that is different during the day and at night. The system is seen to invest in intelligent thermal storage to take advantage of these opportunities. Contrary to expectation, houses with lower insulation show greater potential for storage use. This is due to higher space heating demand in these houses enabling a higher potential benefit in absolute terms. Since both investment and operation is considered, the model can prioritise heat pump during periods with low marginal costs and shift it away from peak periods.

Another set of models consider integration of the operational aspects of both the electricity supply side and the electrical heating devices in the consumer side into one monolithic optimisation problem. The work of (Patteeuw, Reynders, et al., 2015) determines the carbon dioxide abatement cost of residential heat pumps with active demand side response. The authors compare the abatement cost of installing a heat pump instead of a natural gas boiler. The heat pump is also equipped with a thermal energy storage unit. The structure of this problem is as follows.

The objective function is to minimise the operating cost of conventional generators. This is subject to several constraints. The power balance constraint accounts for conventional and renewable generation on the supply side and fixed and flexible demand on the consumer side. There are several factors such as ramping, minimum up time and minimum down time that need to be accounted for the generators to operate. Finally the heating devices also have associated constraints such as capacity, coefficient of performance and storage capacity.

This optimisation problem is solved with a time step of one hour over a planning horizon that is one week long. The results are meant to provide an upper bound on the potential emissions savings that can be attained through the use of this technology. The future scenario based on Belgium is dominated by Combined Cycle Gas Turbines and Open Cycle Gas Turbines with comparatively lower levels of renewable penetration. Only single family residential households are considered on the consumer side. The results indicate that heat pump deployment decreases renewable curtailment. Though heat pumps contribute to peak demand, the use of demand response helps counter these effects. The level of renovation has a strong influence on emission savings. Abatement costs for mildly renovated buildings are high since emission savings are low. Thoroughly renovated buildings on the hand result in much lower abatement costs and emissions. Application of demand response is seen to reduce emissions and peak demand at the household level. A similar model is employed in (Patteeuw, Bruninx, et al., 2015) with the inclusion of resistance heating in addition to heat pumps. The authors also discuss different representations of the supply side such as a detailed unit commitment model and a merit order dispatch model. Merit order models are seen to provide a good approximation of performance at considerably lower computation times. For this reason, the merit order representation is used in (Arteconi et al., 2016) to study the impact of market penetration of demand response enabled devices. Increased penetration drives the overall operational costs down. This study also investigates the changes in economics of the individual household. As penetration increases, the extent to which the individual consumer has to react decreases. Hence, the savings decrease from the household perspective.

In a variation from the previous references which studied the use of electrical heating, the work of (Alahäivälä, Heß, Cao, & Lehtonen, 2015) considers a cogeneration system. The thermal energy storage tank has been equipped with a resistive heater in order to increase demand in case the situation calls for it. The cogeneration unit uses an internal combustion engine as its prime mover. A natural gas boiler is installed as a fall back. Heat demand is generated using a dynamic building simulation model. Hourly electricity prices are extracted from the electricity spot market. In this case the consumer can also play the role of generator due to the cogeneration system. The question is whether the occurrence of surplus electricity will diminish the economic case for the cogeneration unit. Since a present day energy system is considered, the frequency of occurrence of surplus generation (and hence low electricity prices) is not high and the carbon intensity of the central grid is high. Thus these factors do not impede operation and the performance improves when optimal control is used to control this setup.

The provision of demand response from a cogeneration unit based on a price signal has also been studied by (Houwing, Negenborn, & Schutter, 2011). The focus of this study is on the economic performance or the reduction in costs due to the installation if the cogeneration unit. Comparisons are made between a typical heat led strategy and an intelligent operating strategy based on model predictive control. Cogeneration units perform best when there is a large difference between electricity and gas prices. When real time electricity prices are used this value is diluted. Hence it was observed that strongly fluctuating electricity prices provide more scope for intelligent control and hence reduce costs to a larger extent in comparison to the baseline control strategy. The model predictive control strategy is seen to produce energy costs that are one to fourteen per cent lower than that of the heat led strategy.

2.3.4.3. Analysis and Way Forward

The scope of this work revolves around three factors. First is the context of power system decarbonisation. Second is the use of a decentralised electricity price signal which is set to zero to incentivise consumption when surplus renewables are encountered. Finally, this thesis considers the comparison of performance of electrical heating and cogeneration for an individual household using optimised control. The intersection of these three factors is virtually untreated by previous literature.

Power system decarbonisation is the central theme of this thesis. Hence this thesis differentiates itself from (Alahäivälä et al., 2015; Arteconi et al., 2016; Houwing et al., 2011; Patteeuw, Bruninx, et al., 2015; Patteeuw, Reynders, et al., 2015) in this respect. Although the work of (Patteeuw, Bruninx, et al., 2015; Patteeuw, Reynders, et al., 2015) and (Arteconi et al., 2016) make use of a future scenario, they do not incorporate an energy mix which is dominated by low carbon sources into the model. Similarly, only present day energy systems are considered by (Alahäivälä et al., 2015) and (Houwing et al., 2011).

Next let us consider the decentralised electricity price signal which is set to zero at times. The works of (Patteeuw, Bruninx, et al., 2015; Patteeuw, Reynders, et al., 2015) and (Arteconi et al., 2016) assume that a single centralised coordinator has complete control over and knowledge about all the flexible resources connected to the system at all points of time. This is not practical due to large computational costs when several million units are involved. Issues related to privacy are another important drawback of this approach.

Other references which analyse overall energy systems (Hedegaard & Balyk, 2013; H. Lund & Münster, 2003) use aggregated representations of flexible resources since individual representation of all devices is not feasible. This representation also implicitly assumes that a centralised entity has control over all heating devices. (Budischak et al., 2013) make use of if then rules to displace natural gas in the residential sector as a whole when renewable generation is in excess of load and storage capacity. This simplifying assumption is made since management of residential heating is not the focus of this study. Nevertheless this assumption also signifies centralised control. Another variant of such an aggregated representation can be found in (Papaefthymiou et al., 2012) where information from one reference building is scaled up to be incorporated into the unit commitment model. As this one building is the only deciding factor in this case it implies that all heating devices are controlled en masse, making it another centralised model.

It can be argued that (Pensini et al., 2014) is very close to the scope of this work as it studies power system decarbonisation and the displacement of heating fuels. Firstly, this reference makes use of an aggregated thermal load; hence it does not provide a tool for coordinating multiple resources. Secondly, it only considers electric heating and does not compare performance of cogeneration units. This is also true of (Arteconi et al., 2016; Hedegaard & Balyk, 2013; Papaefthymiou et al., 2012; Patteeuw, Bruninx, et al., 2015; Patteeuw, Reynders, et al., 2015).

3. Impact of Power System Decarbonisation on Electricity Price

The contents of this chapter are adapted from the following publication:

Vijay, A., Fouquet, N., Staffell, I. and Hawkes, A., 2017. The value of electricity and reserve services in low carbon electricity systems. Applied Energy, 201, pp.111-123.

3.1. Introduction

There is a general consensus that a decarbonisation of electricity systems is fundamental in the global transitions (Clarke et al., 2009; IPCC, 2014; Kriegler et al., 2014). In scenarios that consider the possible make-up of future electricity systems, decarbonisation is typically achieved via a combination of nuclear power, carbon capture and storage (CCS), and renewables such as bioenergy, wind, solar, and marine sources (R. Kannan, 2009).

Electricity systems dominated by low carbon generation differ greatly from most present-day systems. Particularly, they impose to two new characteristics: inflexibility (relatively constant output from nuclear, or predictable but uncontrollable output from marine energy) and intermittency (fluctuating output from wind and solar). As the penetration of these sources increases, market price dynamics can change significantly, as evidenced by the emergence of occasional negative electricity prices in several countries (Ederer, 2015). Ultimately changes will influence the overall energy mix and electricity system greenhouse gas emissions (Barteczko-Hibbert, Bonis, Binns, Theodoropoulos, & Azapagic, 2014; Kazagic, Merzic, Redzic, & Music, 2014). Given the importance of prices for long-term investment decisions, and on a vast array of end-use technologies and decentralised energy resources, there is a pressing need for technically-grounded analytical tools to understand the complex relations between future electricity system design and the prices it will yield.

3.1.1. Structure of the Unbundled Electricity Market in the UK

The British electricity system had around 357 TWh annual and 53 GW peak demand; out of which 24.5% was supplied by renewables in the year 2016 (BEIS, 2017a). The structure of a typical unbundled electricity market consists of four segments: generation, transmission, distribution and retail. In the British market, the first and the last segments are competitive with many players competing for market share. Transmission and distribution are natural monopolies, and as such are often regulated or state-owned and operated.

Simplistically, trade of electricity between generators and retailers mainly consists of bilateral agreements and over the counter (OTC) trades, power exchange trades and the balancing mechanism (National Audit Office, 2014). Bilateral trades can happen years in advance. Power exchange trades happen days or hours in advance, up to the point of 'gate closure' which is one hour before delivery in the British market (Harris, 2011). The spot market operates in half-hourly segments.

Electricity contracts are frozen one hour before physical delivery. Trading parties can no longer make any changes to their contracted positions (i.e. level of generation). The contracted positions at this point are known as Final Physical Notifications (FPN). The balancing mechanism primarily operates in the period between gate closure and the end of the settlement period, and is intended to fine-tune generation such that it is equal to demand at any moment. The trading parties must only deviate from their contracted positions at the instruction of the System Operator (National Grid) where they are participating in the balancing mechanism, or otherwise face penalty charges known as imbalance pricing (Elexon Limited, 2016).

3.1.2. Novelty and Contribution

This chapter takes a bottom-up engineering-economic approach to estimate future electricity prices. By modelling the price formation process, it is capable of capturing the effect of the radical change in the make-up of electricity systems that could occur over coming decades. Hence this work performs an analysis of the impact of a transformation of the electricity grid on electricity prices, which has not been studied by previous literature.

A novel electricity price model is developed. This model uses post processing to yield the short run marginal cost of generation which better represents the characteristics of actual wholesale electricity prices. The post processing algorithm incorporates the cost of start-up and pumped storage into the wholesale electricity price calculation which is not considered in other models.

3.2. Methodology and Data

This section describes two pre-existing approaches which are compared to the novel model developed by this chapter. The unbundled electricity market in the UK has been considered as a case study.

3.2.1. Existing Approaches

3.2.1.1. Econometric Predictions

Autoregressive eXogenous (ARX) modelling is a widely accepted econometric approach originally proposed by (Misiorek, Trueck, & Weron, 2006) and later used in several studies (Gaillard, Goude, & Nedellec, 2016; Kristiansen, 2012; Maciejowska, Nowotarski, & Weron, 2016; Nowotarski, Raviv, Trück, & Weron, 2014; Rafał Weron & Misiorek, 2008; Ziel, 2016).The model structure is given by the formula:

$$p_t = \phi_1 p_{t-24} + \phi_2 p_{t-48} + \phi_3 p_{t-168} + \phi_4 mp_t + \psi_1 z_t + \sum_{i=1}^{3} d_i D_i + \varepsilon_t \tag{13}$$

Here p_t is the natural logarithm of the electricity spot price, the lagged log-prices p_{t-24}, p_{t-48} and p_{t-168} account for the autoregressive effects of previous days for the same hour on a day before, two days ago and a week ago and mp_t represents the minimum price encountered in the previous day. The exogenous component z_t refers to the log-load forecast. The three dummy variables – D_1, D_2 and D_3 (for Monday, Saturday and Sunday, respectively) – account for repetitive weekly patterns. Finally, the ε_t term is assumed to be a set of independent and identically distributed normal variables.

3.2.1.2. Merit Order Stack

The merit order stack is a simple ranking of different generator units by short run marginal cost for power dispatch (Poncelet, Delarue, Six, Duerinck, & D'haeseleer, 2016; Ries, Gaudard, & Romerio, 2016; Staffell & Green, 2016). It is used to determine resource use, under the assumption that units with the lowest marginal cost are dispatched first, with the later units being dispatched in increasing order of marginal cost until generating capacity equals demand. This yields the least-cost solution, but neglects all inter-temporal constraints (ramp rates, start-up times and costs) and transfers (storage and demand side management). The short run marginal cost of electricity corresponds to the marginal cost of the most expensive generator that is active.

3.2.1.3. Limitations of Existing Approaches and Improvements

Econometric methods assume that future trends can be determined solely from the way the system functioned in the past. Such assumptions require large banks of data and are suitable for short term predictions where the nature of the system remains the same. But when there are major changes in the factors that determine electricity market operation, namely a transition to a much lower carbon future, such relations no longer hold good. This change is partly addressed by the merit order stack which accounts for the modifications in the energy mix. It is designed to yield the least-cost solution, but neglects all inter-temporal constraints such as ramp rates, start-up times and transfers such as storage. The model described by this chapter improves upon these existing approaches. It is better than an econometric approach since the model does not use historical data but a technical description of the power dispatch system which is more suitable for the objectives of this work. It goes beyond the merit order approach since it contains a more detailed mathematical description of the operation of the power system.

3.2.2. New Approach

This work uses a unit commitment problem to determine the marginal cost of generation. Short run marginal cost is an economic concept related to the extra cost of producing a small incremental amount of a product. In a competitive market, price will be equal to the short run marginal cost (Stoft, 2002). The wholesale price of electricity will therefore be a function of the generators which are online at a particular point of time. This is a justifiable assumption as evidenced by the model validation shown in Section 3.3.1 for the year 2015. The short-run nature of pricing does not discount the ability of the model to manage long term and medium term scenarios. The deciding factor while determining the price of electricity will be the energy mix of the future scenario. This has been adequately represented by the equations and inputs that govern model operation as explained below. However, long term decisions such as capacity planning and infrastructure investment are outside the scope of this work. It should be noted that this work classifies solar and wind generators as intermittent sources which can be curtailed if necessary and nuclear as inflexible generation with very limited ramping capacity. The details of this model formulation are presented below.

3.2.2.1. Problem Statement

An overview of the model used in this chapter is presented in Table 2.

Table 2 - Problem statement for Chapter 3

Inputs	Model	Outputs
Demand Profile Renewable Generation Profile Energy Mix Generator Specifications Fuel Price Carbon Price	Objective: Minimise Cost of Operation Constraints: Load Balance Feasible Operating Envelope	Generator Output Level Electricity Price Profile

The electricity price profile produced by the model is then compared to actual electricity prices to calculate an error index. This error index is used to evaluate whether the proposed approach produces reasonable results.

The unit commitment or power dispatch model is based on the formulation by Arroyo and Conejo (Arroyo & Conejo, 2000). The Arroyo and Conejo model model is not explicitly meant to calculate electricity price. This thesis modifies Arroyo and Conejos's formulation according to the application considered here since a complicated model did not result in a lower error index. Changes include using linear approximations in place of piece-wise linear expressions, usage of a constant start-up cost in place of an expression dependent on time since last shut down and removal of minimum up time and minimum down time. This thesis also extends this model by adding a post processing sequence to incorporate start-up costs and operation of pumped storage into the wholesale price of electricity.

3.2.2.2. Dispatch Model Formulation

The model consists of an objective function and a set of constraints. The objective function is made up of fuel, carbon and start-up costs as shown in Equation (14). The first constraint shown in Equation (15) governs energy balance between the sources, storage and load. The next constraint shown in Equation (16) represents the feasible operating envelope of thermal power plants. The last constraint shown in Equation (17) represents the feasible operating envelope of the pumped storage units.

$$Minimize \sum_{j \in J} \sum_{t \in T} \left(c_{j,t}^{fuel} + c_{j,t}^{carbon} + c_{j,t}^{startup} \right) \tag{14}$$

Subject to,

$$\sum_{j \in J} (p_{j,t}) + p_t^{solar} + p_t^{wind} + q_t \ = D_t, \forall t \in T \tag{15}$$

$$p_{j,t} \in \Pi_{j,t}, \forall t \in T, \forall j \in J \tag{16}$$

$$q_t \in \Gamma_t, \forall t \in T \tag{17}$$

Where $c_{j,t}^{fuel}$ is the fuel cost of unit j in period t, $c_{j,t}^{carbon}$ is the carbon cost of unit j in period t, $c_{j,t}^{startup}$ is the start-up cost of unit j in period t, $p_{j,t}$ is the electricity generated by thermal unit j in period t, p_t^{solar} is the electricity from solar sources in period t, p_t^{wind} is the electicity from wind sources in period t, q_t is the electricity consumed or released by pumped storage, $\Pi_{j,t}$ is the feasible operating envelope for thermal generator units and Γ_t is the feasible operating envelope for pumped storage. Details regarding mathematical modelling of these constraints are presented below.

The output of a thermal power plant has to lie between its upper and lower limits as shown in Equation (18). The binary variable associated with the active state of a thermal power plant is also governed by the same relation.

$$\underline{P_j} \phi_{j,t}^{on} \leq p_{j,t} \leq \overline{P_j} \phi_{j,t}^{on}, \forall t \in T, \forall j \in J \tag{18}$$

Where $\underline{P_j}$ is the minimum generation of thermal unit j, $\overline{P_j}$ is the maximum generation of thermal unit j and $\phi_{j,t}^{on}$ is the on or off indicator of thermal unit j in period t. Consecutive output levels are constrained by the ramp up and ramp down limits as shown in Equations (19) and (20).

$$p_{j,t} - p_{j,t-1} = R_j^u, \forall t \in T, \forall j \in J \tag{19}$$

$$p_{j,t-1} - p_{j,t} = R_j^d, \forall t \in T, \forall j \in J \tag{20}$$

Where R_j^u refers to the ramp-up limit of unit j and R_j^dcorresponds to the ramp-down limit of unit j.

Power from solar and wind sources have to lie between upper and lower limits as well as shown in Equation (21) and (22). This implies that some curtailment is possible.

$$\gamma_s R_t^{solar} \leq p_t^{solar} \leq R_t^{solar}, \forall t \in T, \forall j \in J \tag{21}$$

$$\gamma_w R_t^{wind} \leq p_t^{wind} \leq R_t^{wind}, \forall t \in T, \forall j \in J \tag{22}$$

Where R_t^{solar} is the total solar electricity generation in period t, γ_s is the share of solar capacity that cannot be curtailed, R_t^{wind} is the total wind electricity generation and γ_w is the share of wind capacity that cannot be curtailed. The relation between start-up, shut down and active state indicators is governed by Equation (23).

$$\phi_{j,t}^{su} - \phi_{j,t}^{sd} = \phi_{j,t}^{on} - \phi_{j,t-1}^{on}, \forall t \in T, \forall j \in J \tag{23}$$

Where $\phi_{j,t}^{su}$ is the start-up indicator for unit j in period t, $\phi_{j,t}^{sd}$ is the shutdown indicator for unit j in period t and $\phi_{j,t}^{on}$ is the on or off indicator for unit j in period t. Fuel and carbon costs increase linearly with generation as shown in Equations (24) and (25).

$$c_{j,t}^{fuel} = A_j^f \phi_{j,t}^{on} + F_j^f p_{j,t}, \forall t \in T, \forall j \in J \tag{24}$$

$$c_{j,t}^{carbon} = A_j^c \phi_{j,t}^{on} + F_j^c p_{j,t}, \forall t \in T, \forall j \in J \tag{25}$$

Where A_j^f and F_j^f are linear coefficients of fuel cost and A_j^c and F_j^c are linear coefficients of carbon cost. Start-up cost is the product of the start-up cost level and the start-up indicator as shown in Equation (26).

$$c_{j,t}^{startup} = L_j \phi_{j,t}^{su}, \forall t \in T, \forall j \in J \tag{26}$$

Where L_j is the start-up cost of unit j. Pumped storage units act as storage buffers of energy. They have two modes of operation, pumping mode and generation mode. In pumping mode they consume power in order to increase the energy stored. In generation mode, they release the energy stored to supply power.

The constraint governing storage level is represented by Equation (27). The charging and discharging rates are multiplied by half since the storage level is measured in MWh and the duration of each time interval is one half hour.

$$e_t = e_{t-1} + 0.5\left(\eta^p q_t^p - q_t^g / \eta^g\right) \tag{27}$$

Where e_t is the storage level of pumped storage, η^p is the efficiency of pumped storage in pumping mode, η^g is the efficiency of pumped storage in generating mode, q_t^p is the electricity consumed by pumped storage in pumping mode and q_t^g is the electricity released by pumped storage in generating mode. The limit on total capacity is governed by Equation (28).

$$e_t \leq E^{max} \tag{28}$$

Where E^{max} represents the total capacity of pumped storage, The charging and discharging of pumped storage is represented by two non-negative variables in Equations (292929).

$$q_t = q_t^g - q_t^p \tag{29}$$

Where q_t is electricity released or consumed in period t. The bounds on inflow and outflow are represented by Equation (30) and Equation (31).

$$0 \leq q_t^g \leq U^g \phi_t^g \tag{30}$$

$$0 \leq q_t^p \leq U^p \phi_t^p \tag{31}$$

Where U^g is the maximum discharge limit, ϕ_t^g is the generating mode indicator, U^p is the maximum charging limit and ϕ_t^p is the charging mode indicator. The mode clash constraint, Equation (32), prevents the problem from simultaneously operating in pumping and generating mode.

$$\phi_t^g + \phi_t^p \leq 1 \tag{32}$$

The level of storage at the end of the planning horizon is constrained to be equal to the level at the beginning by Equation (33), to avoid giving the system any cost-free energy.

$$e_0 = e_{T^{end}} = 0 \tag{33}$$

3.2.2.3. Post Processing Sequence

Although the merit order stack provides a reasonable first estimate of marginal cost, it ignores many constraints which are an integral part of power dispatch as discussed in the previous section. The proposed method makes use of the unit commitment problem to account for the constraints neglected, followed by post-processing steps to distribute costs that are not observable directly from the unit commitment solution. It consists of three steps:

Stage 1: The sum of slopes of linear objective terms, fuel cost and carbon cost are calculated for the generator units active in each period.

Stage 2: For each generator, cost for each start-up is attributed to time periods. The level of price increase is calculated as the start-up cost divided by the total generation over the period that the unit was active after that start-up.

Stage 3: Contributions from pumped storage are assigned marginal costs. This is based on a weighted average of the marginal costs derived from the previous steps when the unit was charging. The weights are assigned according to the charging profile and an efficiency penalty is applied to account for the turnaround efficiency of pumped storage.

The first step allows the method to account for minimum/maximum generation limits and ramping limits. The second and third steps account for start-up costs and pumped storage respectively.

A Matlab style pseudo code has been provided to explain the sequence in more detail:

```
% Fuelslope contains the slope associated with fuel cost for each
% generator. Carbonslope contains the slope associated with carbon cost for
% each generator. Poweroutput contains the results of the power dispatch
% problem related to output of each generator.

marginals = zeros(xn,yn);
for i = 1:number_of_generators
   for j = 1:number_of_periods
      if Poweroutput(i,j) > 0
         marginals(i,j) = Fuelslope(i) + Carbonslope(i);
      end
   end
end

% start_up_matrix is another result from the power dispatch problem. It
% contains information about when each unit was started up and how much
% cost was incurred.
```

```
for i = 1:size(Poweroutput,1)
   start_ups = find the periods in which the unit was started up
   for j = 1:length(start_ups)
      end_index = find the period till which the unit was operational after current start up
      increment = start_up_matrix(i,start_ups(j))/sum( 0.5*Poweroutput(i,start_ups(j):end_index) );
      marginals(i,start_ups(j):end_index) = marginals(i,start_ups(j):end_index) + increment;
   end
end

% pumpedstorage is an output from the power dispatch problem. It contains
% information about the magnitude and timing of charging and discharging
% actions. Charging is positive and discharging is negative.

current_period = 1;
previous_volume = 0;
previous_price = 0;
efficiency = 0.81;
marginalStorage = zeros(number_of_periods,1);
while ( current_period < number_of_periods
            and
      pumped storage was discharged between the current period
      and the end of the day )

   start_index = find when discharging started
   end_index = find when discharging stopped
   volumes = pumpedstorage(current_period:start_index);
   prices = max(marginals(:,current_period:start_index))';
   weighted_average = ( sum(volumes.*prices) + previous_price*previous_volume )/…
   ( sum(volumes) + previous_volume);

   marginalStorage(start_index:end_index) = weighted_average/efficiency;

   prevprice = weighted_average;
   revised_volume = Add charging and discharging actions till current period to previous_volume
   previous_volume = revised_volume;
```

```
  current_period = end_index + 1;
end

overall_marginal = max([marginals;marginalStorage'])';
```

3.2.2.4. Mark Up

In a perfect market, generators' bids would be close to their short run marginal cost. But in practice it is observed that generators tend enter slightly higher bids with the difference increasing as the load approaches peak demand (Eager, Hobbs, & Bialek, 2012). Hence we include an exponential mark-up scheme in order to improve the error performance of the model (Eager et al., 2012):

$$P_m + ae^{bC} = P_h \tag{34}$$

Here P_m is the short run marginal cost determined from the approaches described earlier, P_h is the actual value of market price encountered and C is the capacity margin or the excess of the installed generation over demand. Parameters a and b are chosen such that the difference between the two sides of Equation (34) is minimised to give an empirically observed mark-up for wholesale electricity prices in the British market.

3.2.3. Error Index

In order to evaluate performance of the models, we make use of the Weekly-weighted Mean Absolute Error (WMAE) [51, 52, 63, 64]. Modifications have been made to incorporate half hourly time resolution. This measure has been chosen since it has the benefit of not resulting in large values of error when the market price is near zero. It is defined as,

$$WMAE_i = \frac{1}{336 \cdot \bar{P}_{336}} \sum_{h=1}^{336} \left| P_h - \hat{P}_h \right| \tag{35}$$

Here P_h is the actual price for half hour h, $\hat{P}_h$ is the predicted price for that half hour, $\bar{P}_{336} = \frac{1}{336} \sum_{h=1}^{336} P_h$ is the mean price for a given week and 336 is the number of half hours in a week. This error index will be calculated for each of the existing approaches. This provides a yardstick to measure performance of the different models used. Details are presented in Section 3.3.1.

3.2.4. Data Used in the Simulations

The methods and equations described in the previous sections are applied to assess the electricity grid in UK. Half-hourly resolution time series data for demand and renewable in-feed were taken from publicly available sources (Elexon Limited, n.d.-b, n.d.-a). Fuel prices were taken from market data related to ICE API2 CIF ARA Index for coal, TR Natural Gas NBP UK Index for gas and the London Brent Crude Oil Index for oil (Thomson Reuters, 2016). Fuel prices for the year 2035 are based on the Updated Energy and Emissions Projections for the year 2015 released by the Department of Business, Energy and Industrial Strategy in the UK(BEIS, 2015). Generator capacities are based on Final Physical Notifications from (Elexon Limited, n.d.-b, n.d.-a) and generator efficiencies are based on (Single Electricity Market Committee, 2011).

The energy mix for the year 2015 is based on historic data (Elexon Limited, n.d.-b, n.d.-a). This is then modified for the year 2035 based on the four Future Energy Scenarios (National Grid, 2015) produced by National Grid (the Transmission System Operator), which are summarised in Table 3. Every year National Grid produces a set of Future Energy Scenarios through engagement of stakeholders across the energy sector and beyond. Feedback from nearly two hundred organisations was combined with in-house modelling to generate these scenarios. Gone Green features a five-fold increase in renewables and the total phasing out of coal so that the UK's carbon and renewable targets are met on time. Consumer power exhibits market driven characteristics, prioritising consumer desires over emission levels. The Slow Progress scenario results from a low economic growth rate limiting the society's ability to adopt low carbon technologies. The No Progress scenario represents the business as usual case which is focussed on achieving security of supply at the lowest possible cost. The materially significant renewable sources are wind, solar and biomass. Biomass is small and dispatch-able and so does not add to the problems of the system. Run of river hydro is trivial in the UK at 1.5% of supply and has limited potential for expansion (BEIS, 2013c).

Table 3 - Energy mix summary for year 2015 and National Grid's Future Energy Scenarios for year 2035 (National Grid, 2015)

Fuel-type	**2015 (GW)**	**Gone Green (GW)**	**Consumer Power (GW)**	**Slow Progress (GW)**	**No Progress (GW)**
Nuclear	10.8	14.1	10.7	7.4	4.6
Coal	20.1	0.0	1.9	1.9	3.9
CCS Coal	0.0	4.5	0.4	0.4	0.0
Gas	32.0	24.8	31.5	29.7	42.1
CCS Gas	0.0	1.7	0.4	0.4	0.0
Oil	1.7	1.7	1.7	1.7	1.7
Wind	6.6	49.6	33.6	42.1	27.6
Solar	6.3	25.6	31.6	21.1	12.4
Interconnectors	3.5	17.7	10.8	14.2	9.8

As weather driven renewables are a key feature of these scenarios, they required modelling in detail. Hourly capacity factors for wind and solar power were simulated using the Renewables.ninja platform (S Pfenninger & Staffell, 2016; Staffell & Pfenninger, 2016). This combines global meteorological data from NASA's MERRA-2 reanalysis with physical models of wind and solar farms to yield temporally and spatially explicit profiles of power output which capture the underlying correlations and variability in weather systems and resource availability. Wind speeds at 2, 10 and 50 metres above ground are used by the VWF model to simulate wind farm output, which is validated against metered output data from Britain's wind farms in (Staffell & Green, 2016), and found to be accurate to within ±4.5% of national output at hourly resolution. Solar irradiance and temperature data are used by the GSEE model to simulate solar farm output, as demonstrated in (Stefan Pfenninger & Keirstead, 2015).

Time series were generated for the four capacity projections for 2035 in National Grid's Future Energy Scenarios. It was assumed that solar farms and rooftop PV systems will continue to be installed with the same geographic distribution as they are today, and so the hourly capacity factors were the same across all four scenarios. The distribution of PV panels is already wider than one would naturally expect because installation was supported by generous subsidies which made installation in low-insolation areas (e.g. Scotland) still profitable. Large ground-mounted solar farms which are invested in purely profit-maximising grounds will likely become more widely spread, but roof-mounted panels which have been detached from market forces may not. It is unlikely that the change can be modelled with any predictive capability, and that the geographic shift would have a meaningful impact on results, so this simplifying assumption was made.

Conversely, new wind farms are being built and planned in different areas from the existing fleet, predominantly offshore in the North and Irish seas. National Grid's scenarios specify different shares of onshore and offshore capacity, which relative to 2015 range from a 25–70% growth in onshore capacity and a 2–5.5 fold increase in offshore capacity. A database of current and planned wind farms from (Staffell & Pfenninger, 2016) was used to construct a fleet of wind farms to represent each of the 2035 capacity scenarios. It was assumed that all current farms still operate (or will be repowered to the same capacity), then new farms were randomly selected to be built until the required level of onshore and offshore capacity was reached. It is assumed that wind farms that retire are repowered with newer models, as has happened with around 90% of the UK's wind farms that have reached retirement. This means a new farm, of similar capacity becomes operational at the same location. As with solar it is assumed that like is replaced with like. Farms were first selected from those which have been granted planning permission, and then if further capacity was required, from those which are planned but do not yet have approval. This process of random allocation was repeated ten times for each scenario and was found to yield similar results each time due to the law of large numbers, as the size of individual wind farms is small relative to the total fleet.

The capacity factors for the national wind fleet derived from this process were significantly different between the National Grid scenarios, and those 2035 scenarios are also significantly different from the present day. In line with the findings in (Staffell & Pfenninger, 2016), wind capacity factors are modelled to increase by between a tenth and a quarter from today's levels with the installation of more offshore capacity. The 20-year mean increases from 32.4% with the current fleet (Staffell & Pfenninger, 2016) to between 35.4% (in the No Progress scenario, with 13.4 GW offshore) and 39.9% (in the Gone Green scenario, with 30.3 GW offshore). The pattern of hourly capacity factors also changes depending on the mix of installed farms. The correlation between the No Progress scenario and the current fleet is highest, with R^2=0.987, but for the Gone Green scenario this falls to R^2=0.892 as the substantial amount of North Sea capacity peaks and troughs at different times to the existing onshore mix.

3.2.5. Applicability to Other Energy Systems

While this work makes use of the UK as a case study, this model can be adapted to other energy systems as well. Essentially this involves a change of input parameters to the model. The structure or equations which represent the model do not change. For a new system, one will have to gather time series data for demand, fuel cost data and generator parameters (capacity, ramp limit, efficiency and start-up cost). Renewable output time-series can be generated for any country using the Renewables.ninja platform. This model is capable to representing a wide range of energy mixes using the details presented in this work. Modelling intermittency is taken care of by the time series data for renewable output and inflexibility is a function of the generator parameters specified.

3.3. Results and Discussion

3.3.1. Validation of Modelling Approaches

The dispatch problem considers twelve sample weeks, the first week of each month as the planning horizon, and thus 4,032 half-hourly periods. The price duration curve for these weeks during 2015, for each modelling method is shown in Figure 10. Overall, there is reasonably good agreement between the post-processing and econometric methods and the actual market prices encountered in 2015. It can be seen that the post processing method performs well with the high prices but exhibits a 30 GBP/MWh floor for the lowest priced periods. This behaviour can be attributed to the model structure which considers a single bus system with no transmission constraints. The reason the historic prices fall below the levels observed in the model is due to the need to curtail wind in Scotland because it cannot all be transmitted to England. The Western Interconnector is expected to resolve these transmission constraints when it is completed in 2017 (OFGEM, 2015).

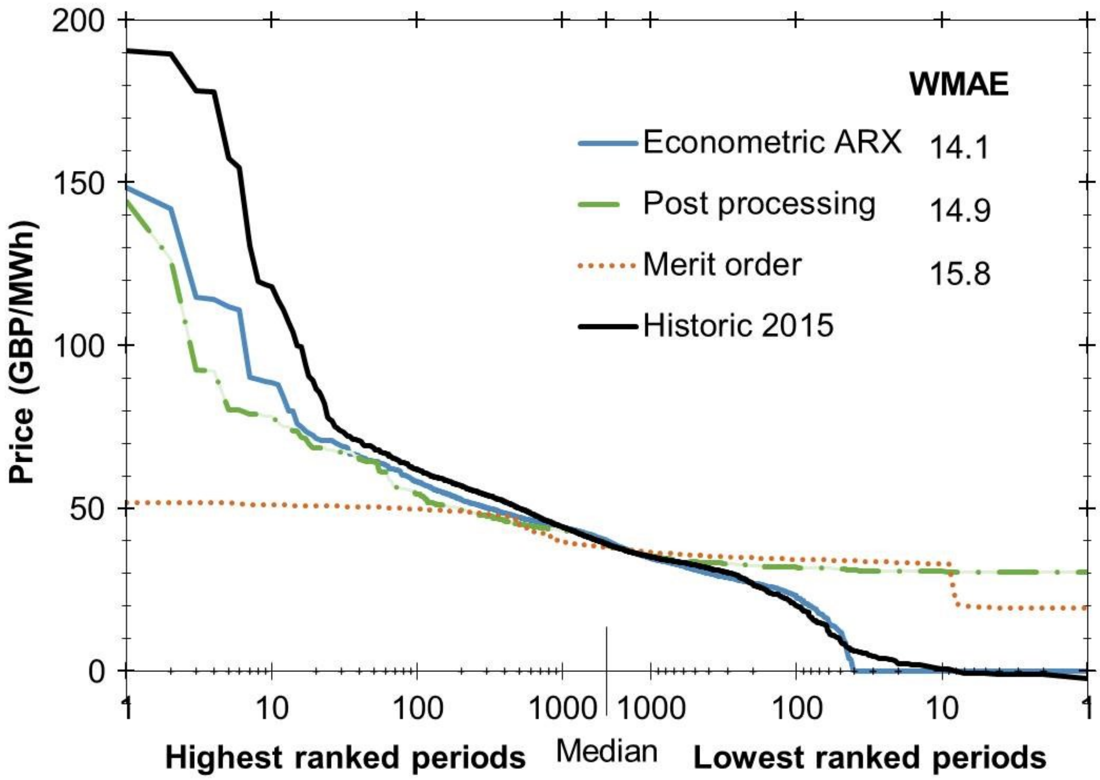

Figure 10 - Price duration curve for electricity prices in the year 2015 (Weekly-weighted mean average errors are shown in the legend, as percentages)

The term $\overline{WMAE}$ is the mean across all weeks for each method, as defined in Section 3.2.3. All of the price data available is used for validation in the post processing method. In contrast, other prediction methods use part of the data for training and part of it for validation. This is not necessary here since our predictions are not based on historic values of price but on a technology rich model of the electricity system. Validation is done by comparing the actual prices to those calculated by the model using the error index defined in Section 3.2.3.

It can be seen from Figure 10 that the econometric method has the least error value of 14.1%. But this is not significantly better than the 14.9% produced by the post processing approach.

While the method presented in this work shows comparable performance to the econometric method, it alone is capable of exploring fundamentally different electricity system technology mixes and look decades into the future. The following section applies the method to the year 2035 using the energy mix data specified in Table 3.

3.3.2. Comparison of Marginal Fuel Types

Distribution of the marginal fuel types is shown in Figure 11. It is clear that the energy mix used has a significant impact on the output of each scenario. In the Gone Green Scenario, with highest renewable penetration, average electricity prices are nearly halved. While the Consumer Power and Slow Progress scenarios show a 12% and 5% increase respectively, the No Progress scenario (which favours fossil fuel) has a 53% increase in mean value of electricity price.

The shift in electricity price can be explained through the analysis of the proportion of each fuel type. Inexpensive units such as renewables and nuclear were marginal in the Gone Green scenario for nearly 65% of the time. The appearance of renewables as the marginal unit implies that no contributions from fossil fuel units were required for 15% of the time in the Gone Green scenario and for 6% of the time in the Slow Progress scenario. The same line of reasoning can be applied to more expensive fuel types as well. CCGT units were marginal for 56% of the time in the No Progress scenario. Prolific usage of gas increases the mean value of electricity price.

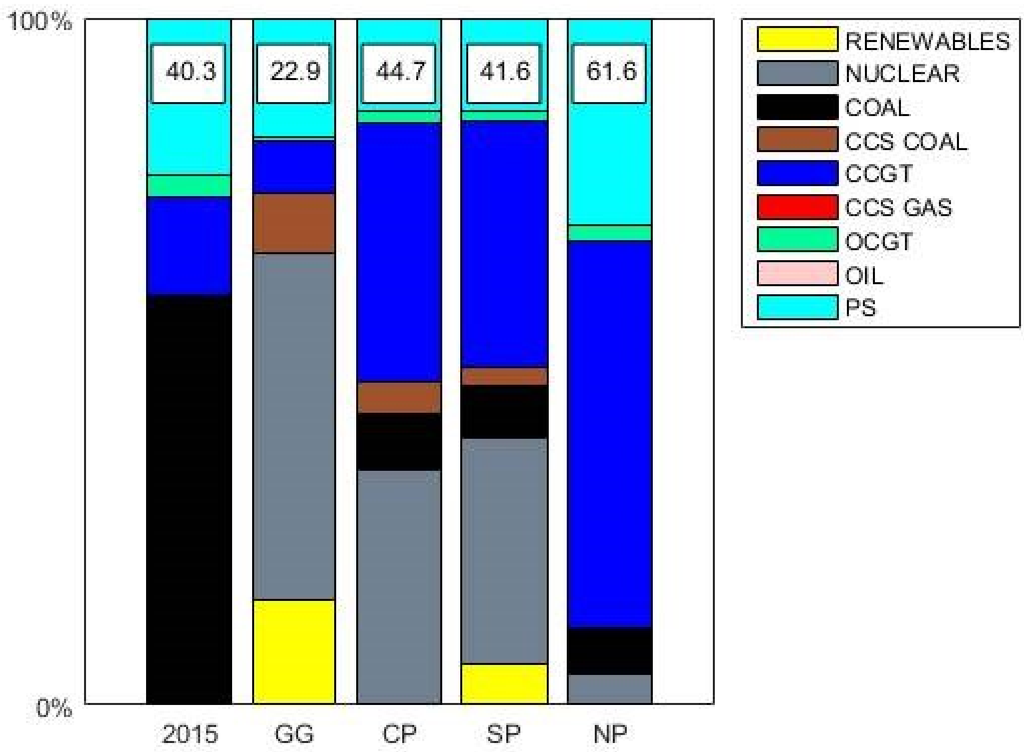

Figure 11 - Distribution of marginal units according to fuel type (Number at the top of the bar is the mean price of electricity for the respective scenario in GBP/MWh, GG – Gone Green, CP – Consumer Power, SP – Slow Progress, NP – No Progress)

3.3.3. Comparison of Marginal Post Processing Stages

Figure 12 indicates whether the units presented were deemed to be marginal due to the three stages described in Section 3.2.2.3: fuel usage and carbon costs (Stage 1), start-up costs (Stage 2) or the implied costs of charging pumped storage units (Stage 3). When referring to different stages as being "marginal" we mean that the generating unit which was deemed to be marginal was so due to the contribution from the corresponding post processing stage. This is to clarify that we are not referring to the stages as technologies themselves. This analysis reveals that the different factors accounted for by the post processing sequence do influence which generating units are marginal.

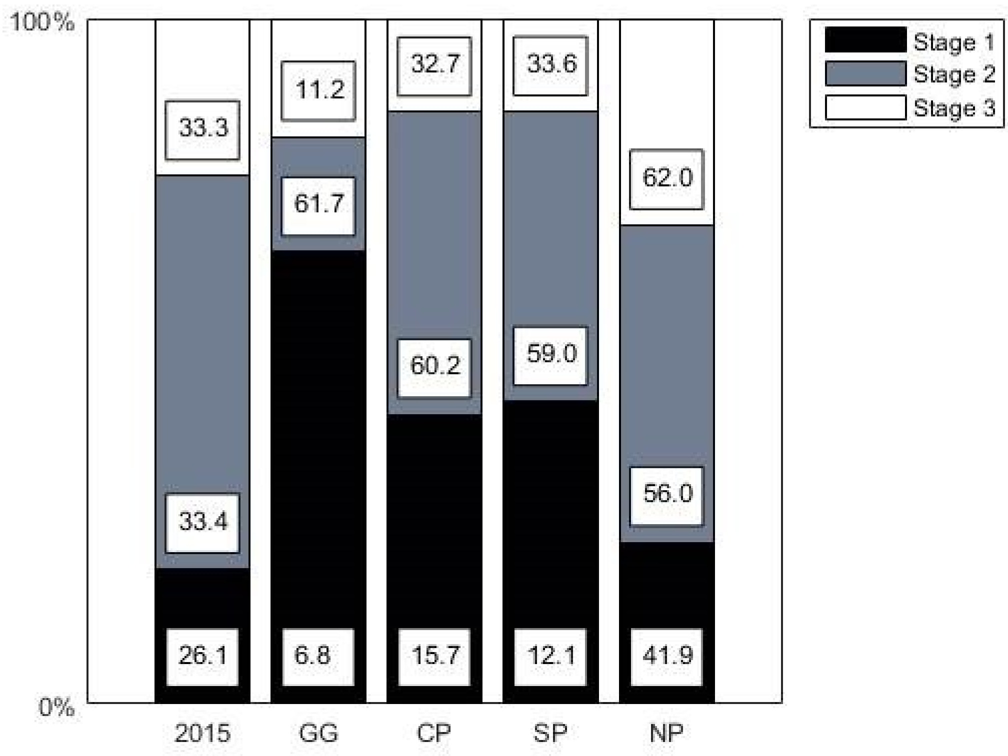

Figure 12 - Distribution of marginal units according to post processing stages (Numbers within the bars indicate the mean value of electricity price in the respective stages in GBP/MWh, GG – Gone Green, CP – Consumer Power, SP – Slow Progress, NP – No Progress)

Stage 1 costs play a major role in the Gone Green scenario, being responsible for 66% of the observed prices. Start-up costs do not figure prominently in the Gone Green scenario, while they play a major role in all of the other scenarios. This can be explained by Figure 13. Having the largest renewables and nuclear capacity among all scenarios, the gone green scenario handles most of its demand by using the two least expensive technologies in terms of variable cost. Hence most of the cases do not require the starting up of thermal units or the use of pumped storage resulting in a smaller proportion of Stage 2 and Stage 3 costs.

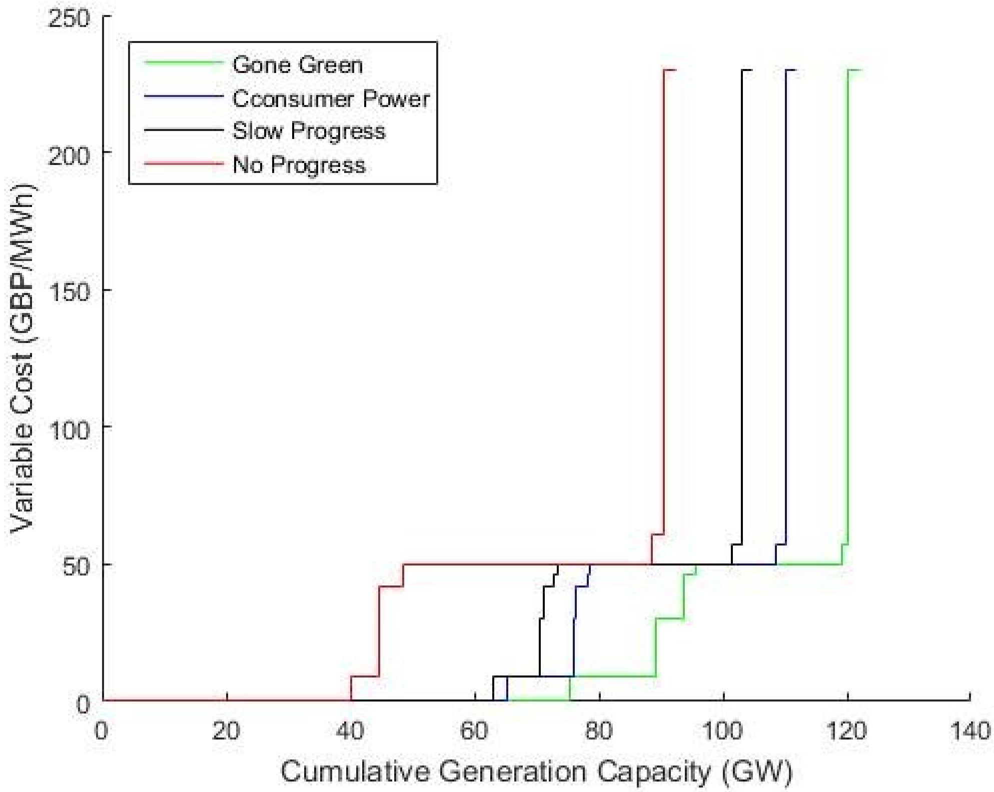

Figure 13 - Merit order stack including renewable generation for all future scenarios

The overall marginal cost is the highest value among the three stages for a given period. It is not necessary that the three stages proceed in increasing order of values as seen from the numbers within the bars in Figure 12. The numbers relate to the mean of the marginal cost for the respective stages. The marginal value for Stage 2 is consistently higher than the other two except in the No Progress scenario. This implies that the impact of start-up cost on electricity price is significantly higher than the fuel and carbon costs (Stage 1) or the implied cost of pumped storage (Stage 3). This is because start-up cost is relatively larger, of the order of thousands of pounds, in comparison to variable pounds which are of the order of tens or hundreds of pounds. The exception in the case of the No Progress scenario is because the generators stay online for longer resulting in a much larger denominator in Stage 2. More details on Stage 2 and Stage 3 are presented later in the later sections.

The variation among post processing stages is better illustrated through Figure 14. This figure shows a snapshot of a day in each of the scenarios. The dispatch decisions are shown in the top row. The Gone Green scenario consists of mostly Stage 1 marginal values marked in Grey in the bottom row. This is because of the high availability of solar and wind power, so only nuclear units are online most of the time. Hence, the implied cost of pumped storage charging is also low as seen by the prices encountered by the Stage 3 blue bands in the bottom row of the Gone Green scenario. In comparison, the renewable output is lower in the Slow Progress and Consumer Power scenarios. The system has to dispatch fossil fuel generators towards the end of the day because of dwindling renewable output. Hence, start-up costs are incurred resulting in Stage 2 post processing value to be higher than the other stages. It is clear that, when active, the Stage 2 values are significantly higher in magnitude corroborating the pattern seen in Figure 12. Another pattern that can be observed is that prices hover around the 60 GBP/MWh mark in the No Progress scenario. This is because the Stage 3 cost for discharging pumped storage which was charged using coal plants is approximately equal to the Stage 2 cost of starting up a large CCGT unit which stays online for 17 hours. Also, the difference between marginal values in the three stages is lesser in the No Progress scenario than those observed in the other scenarios.

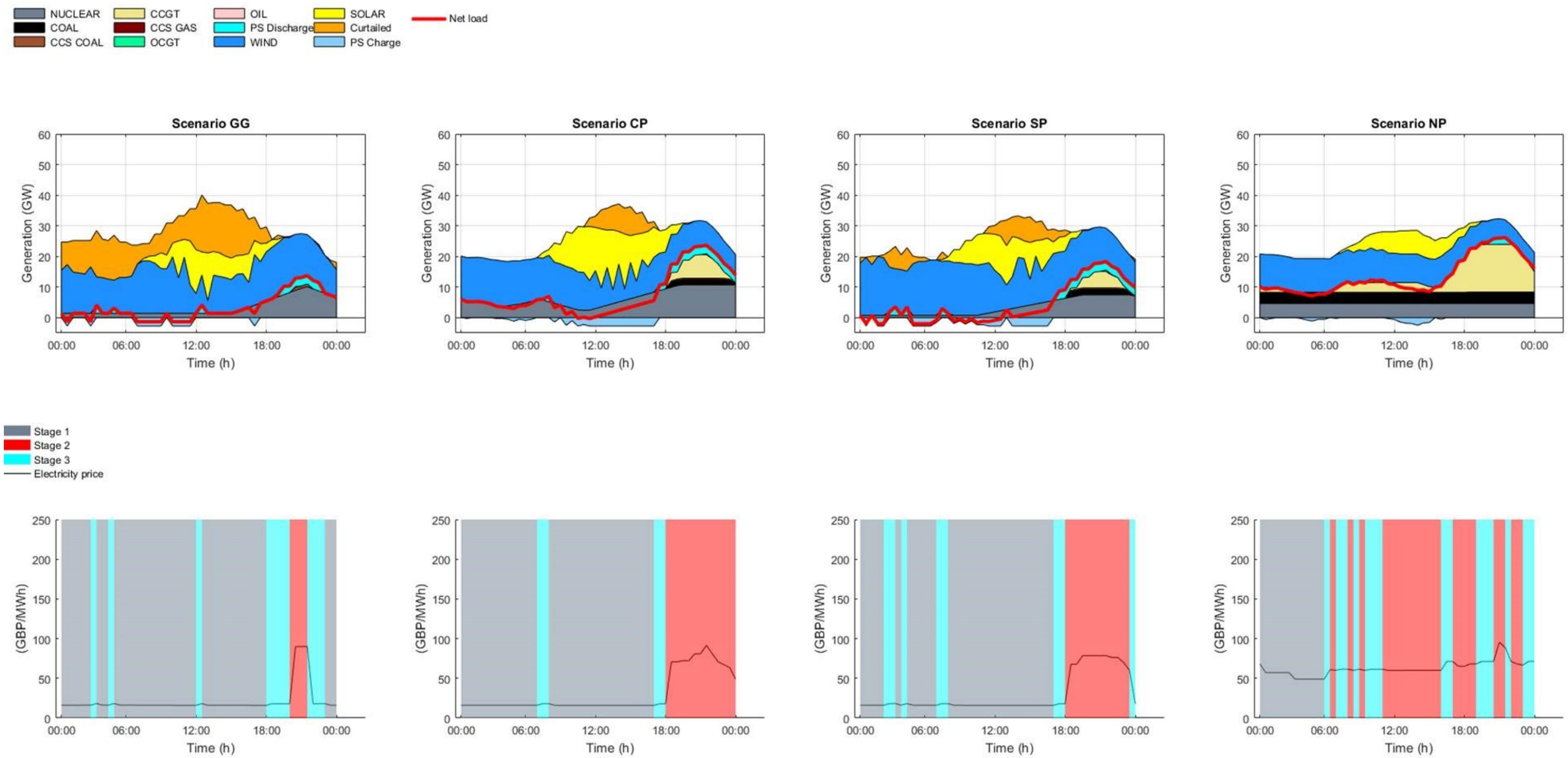

Figure 14 - Comparison of electricity prices in different scenarios (GG – Gone Green, CP – Consumer Power, SP – Slow Progress, NP – No Progress)

3.3.4. Analysis of Stage 2 Marginal Costs

Information regarding the composition of fuel types within Stage 2 is shown in Table 4. The mean value of Stage 2 marginal costs was highest in the Gone Green scenario (61.7 GBP/MWh) and lowest in the 2015 scenario (33.4GBP/MWh) as seen in Figure 12. Stage 2 marginal costs are higher when the unit stays online only for a short period of time. This is due to the fact that the increment in marginal cost due to a start-up is inversely proportional to the amount of energy generated by that unit. Thus the Stage 2 marginal values in the Gone Green scenario are higher since the units stayed online for only 7.1 hours or less. Similarly high mean value of Stage 2 marginal costs are encountered in Consumer Power and Slow Progress scenarios. Generators which were started up in the 2015 and No Progress scenarios stayed online for longer periods of time resulting in relatively lower mean values.

Table 4 - Summary of Stage 2 start-up cost marginal values (MV – Mean marginal value in GBP/MWh, TO – Mean time the unit was online in hours)

	2015		Gone Green		Consumer Power		Slow Progress		No Progress	
	MV	TO	MV	TO	MV	TO	MV	TO	MV	TO
Nuclear	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Coal	30.9	12.4	0.0	0.0	51.4	11.7	52.3	6.1	47.8	15.6
CCS Coal	0.0	0.0	58.7	7.1	54.0	7.3	51.1	5.0	0.0	0.0
CCGT	39.6	8.0	64.8	5.6	62.1	6.4	60.6	3.6	57.1	9.2
CCS Gas	0.0	0.0	64.5	3.0	0.0	0.0	0.0	0.0	0.0	0.0
OCGT	45.0	0.8	64.3	0.6	64.6	0.6	66.0	0.3	69.6	0.7
Oil	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Next, we present a more detailed discussion of the extreme cases, the Gone Green scenario and the 2015 scenario. These two are chosen since the distinctions between present and future scenarios are most clearly visible in these two. The start-up cost per unit output generated is plotted against the time for which they stayed online in Figure 15 and Figure 16. The cycling patterns for the Gone Green scenario reveal that unit start-ups are more frequent (and with lower duration) than in the 2015 system. Most CCS COAL units with high start-up costs only stayed online for 7.5 hours or less, as did large CCGT units. Therefore price spikes are being caused by generators being brought online only to stay operational for brief periods of time after which their services are no longer necessary. A similar plot for the year 2015 is shown in Figure 9. There are much fewer expensive start-ups which stayed online for less than 7.5 hours. The distribution of COAL start-ups is no longer skewed towards the left (low duration). In general, the start-up cost per MWh generated is lower than 50 GBP/MWh.

The reason behind the cycling patterns can be explained by the composition of the energy mix and the working of the optimisation model. The Gone Green scenario which is dominated by renewables and nuclear only requires to start-up units when the nuclear power plants cannot ramp fast enough to provide for the demand encountered. Hence, dispatch-able plants are necessary for security of supply to maintain system stability. With more fossil capacity in the No Progress scenario, plants that are online already have the capacity to ramp their output levels without requiring additional start-ups. Since changes in demand are inputs to the model, it is able to schedule thermal plants such that they stay online for much longer than the Gone Green scenario.

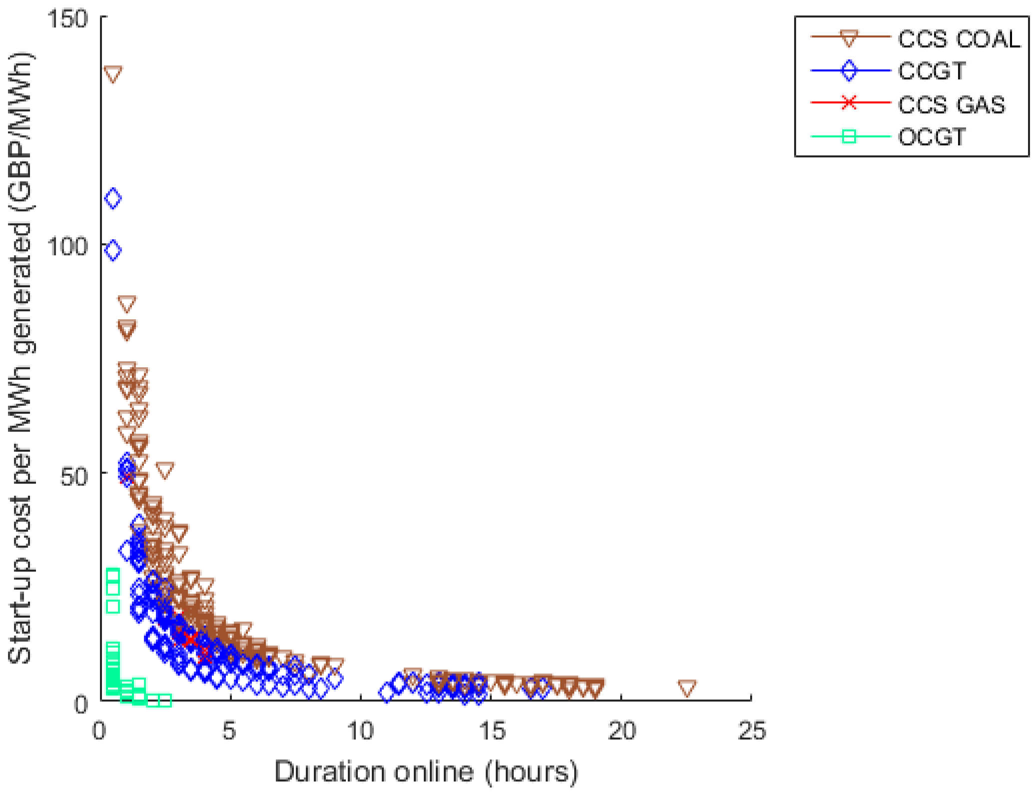

Figure 15 - Plant cycling patterns in the Gone Green scenario

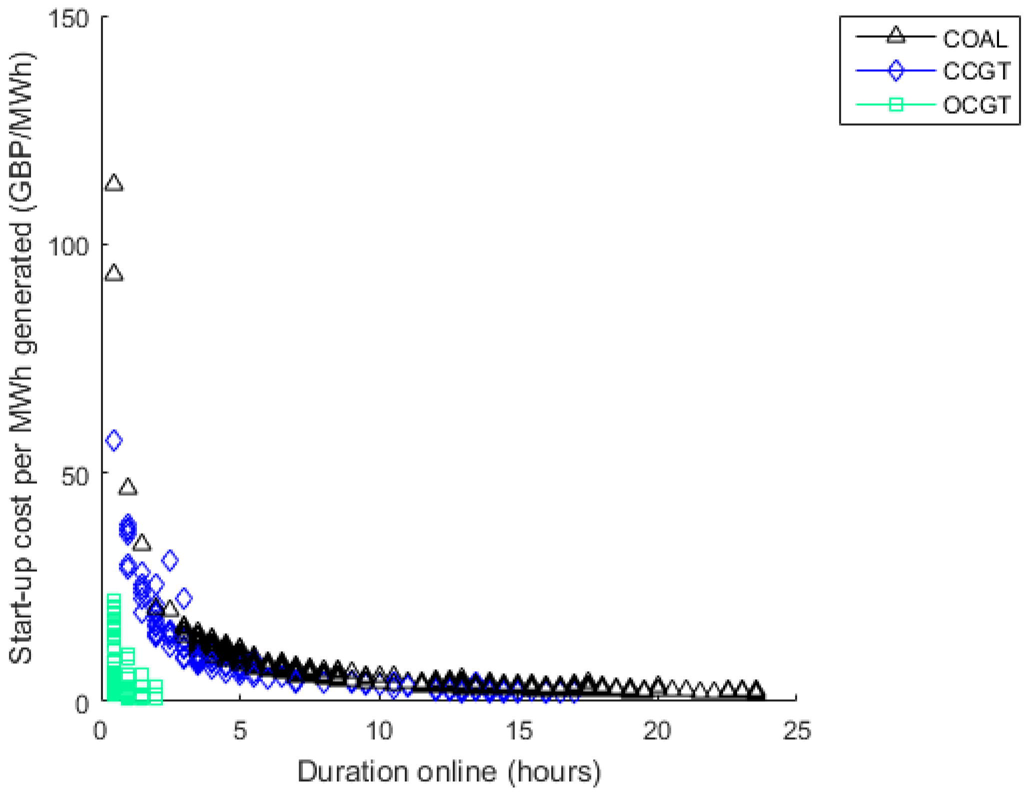

Figure 16 - Plant cycling patterns in the year 2015

3.3.5. Analysis of Stage 3 Marginal Costs

Pumped storage charging patterns are directly related to the implied cost of pumped storage discharge. Figure 12 shows that the average marginal value in the post processing Stage 3 varies across the scenarios. This can be understood through Figure 17, showing the distribution of marginal generation according to fuel type that was used to charge pumped storage. The Gone Green scenario with the lowest value of mean for Stage 3 at 11.2 GBP/MWh was charged predominantly with renewable and nuclear power. Since the price during charging was low, the corresponding implied cost of pumped storage discharge is also low. The highest mean value for Stage 3 is seen in the No Progress scenario at 62 GBP/MWh. Pumped storage charging in this scenario was done mostly using CCGT units and to a lesser extent using coal and nuclear. The other scenarios charging is done through a combination of renewables, nuclear, coal, CCS coal and CCGT units. This wide range of low and high cost fuel types places them at an intermediate mean value.

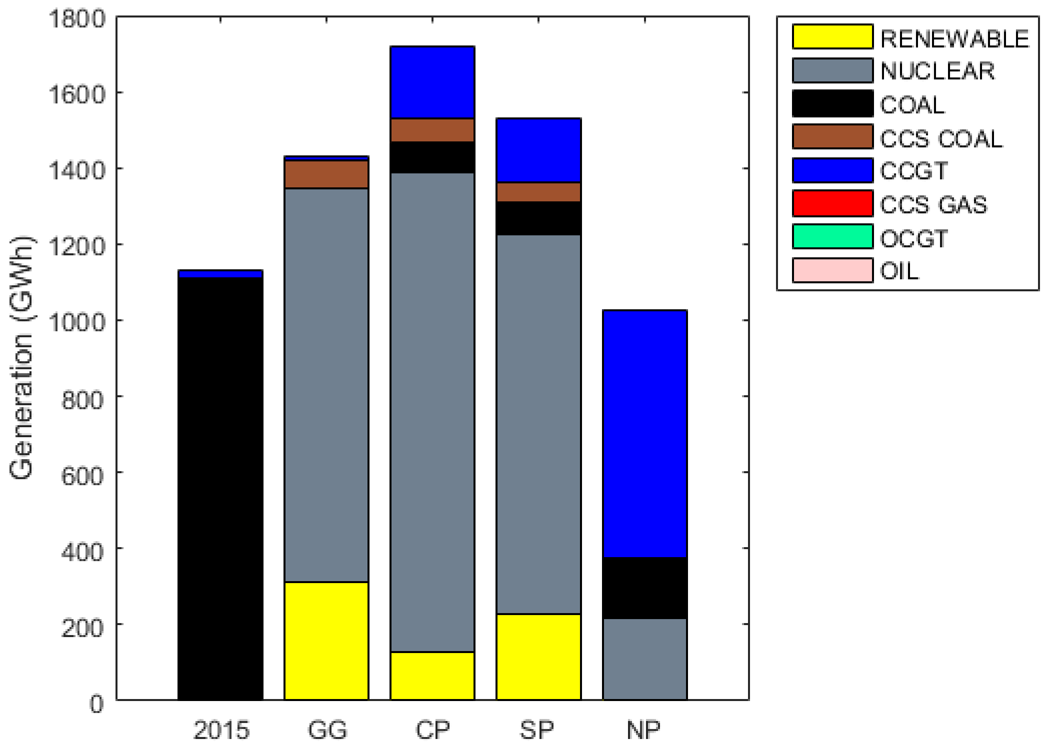

Figure 17 - Marginal generation that was used for charging pumped storage (GG – Gone Green, CP – Consumer Power, SP – Slow Progress, NP – No Progress)

The reasons behind Stage 3 costs can also be explained through the interactions between the global optimiser and the energy mix. As it minimizes the cost of operation, it uses the pumped storage unit to avoid dispatching expensive generators. In the Gone Green scenario this objective results in the optimiser using low cost options as plenty of nuclear and renewable capacity is available. But this is not possible in the No Progress scenario. Since some form of fossil fuel is required in the majority of the cases, charging of pumped storage has to happen via CCGT or coal to avoid dispatch of the more expensive OCGT units.

3.4. Conclusion

This work develops and demonstrates a power dispatch model for calculating electricity prices in low carbon futures. The main contributions are novel methods to describe price formation in the wake of a fundamental transformation of the electricity grid. This work distinguishes itself from other works in its consideration of the overall energy mix rather than just a change in renewable capacity. Another contribution is a UK case study, which establishes that generator operation and market prices will be radically different depending on the evolution of the energy mix. We also explain how the methods used here can be adapted to other energy systems.

We have demonstrated the performance of the model proposed through the validation of data from the year 2015. The dispatch model with post processing can model 2015 prices with an average error of 14.9%, which is comparable to the leading econometric approach (14.1%).

The main policy implication of energy mix transformations is that high penetration of renewables and nuclear is seen to result in weaker market signals in terms of wholesale electricity price. This is seen from the average wholesale price of electricity over the entire year being halved in the Gone Green scenario. In order to keep the dispatch-able plants operational, their revenues may need augmenting through a different market structure.

The price model presented here will be integrated with decentralised energy resources in residential heating systems in the following chapters. A large number of decentralised units can be grouped together to provide services that include both the generation and consumption of power. The resultant generation and consumption of these resources can be controlled by the system operator by using the price signal calculated in this chapter.

4. Residential Heating Systems in Low Carbon Futures

The contents of this chapter are adapted from the following publication:

Vijay, A. and Hawkes, A., 2017. The techno-economics of small-scale residential heating in low carbon futures. Energies, 10(11), p.1915.

4.1. Introduction

The decarbonisation of heat provision is one of the main challenges of broader climate change mitigation (Chaudry et al., 2015). Heat is a significant end-use, for example in the UK space and water heating makes up 24% of final energy consumption and 57% of non-transport energy consumption (BEIS, 2017b). It is also typically relatively carbon intensive, relying on fossil fuels such as natural gas (Chaudry et al., 2015), and is underpinned by long-established and low-cost incumbent technology such as boilers serving demand (Eyre & Baruah, 2015). While alternative technology and fuel options certainly exist for heating, they are generally either significantly costlier (Allen, Hammond, & McManus, 2008), or require infrastructure build in the form of district level heat networks as installing components that cater to individual houses is not economically viable (Jalil-Vega & Hawkes, 2017).

This range of factors makes heat difficult to decarbonise, and therefore an important area of energy research. This is reflected in the literature, with a range of studies exploring the engineering challenges and performance of different heating technologies (Asaee, Ugursal, & Beausoleil-Morrison, 2015; Carlon et al., 2015; Jeremy Cockroft & Kelly, 2006; Dorer & Weber, 2009; González-Pino, Pérez-Iribarren, Campos-Celador, Las-Heras-Casas, & Sala, 2015; Good, Martínez Ceseña, Zhang, & Mancarella, 2016; Hawkes & Leach, 2007; Hawkes, Staffell, Brett, & Brandon, 2009; Herrando & Markides, 2016; Jing, Jiang, Wu, Tang, & Hua, 2014; X. Liu, Lau, Li, & Shen, 2017; Lo Basso, Nastasi, Salata, & Golasi, 2017; Pineau et al., 2013). The vast majority of the studies that consider techno-economics do so in the context of the present-day energy system. However, the energy system within which heating technologies operate is expected to change significantly in the coming decades (Daly & Fais, 2014; IPCC, 2014). In particular, decarbonisation of electricity is seen as a cornerstone of any system-wide climate change mitigation strategy (R. Kannan, 2009). Therefore, it is important and timely to consider heating technologies in the context of this changing system.

One of the developments in a low carbon future that is of importance is the evolution of electricity prices. If the market follows the status quo and is driven by short run marginal cost, it is seen to provide very weak economic incentives for investment in the electricity system. Therefore, it cannot represent a sustainable price to consumers. It is clear that new electricity market signals will be necessary in the future. Generators will need to mitigate the risk associated with low utilisation and low market prices in order to remain viable. One way that risk is currently handled by low carbon generators is through the use of instruments such as Contract for Difference. This provides the low carbon generator with a stable revenue stream in the face of uncertainty. Since such solutions are critical to ensure smooth operation of the electricity grid, this study introduces the use of a fixed power purchase agreement. Generators receive a constant charge for all power they inject into the grid. If this charge is priced by accounting for upfront costs and capacity factor, the revenue generated will able to recover the money invested. This presents a simple and arguably a reasonable way forward for all generators participating in the market. More complex instruments are possible, the design of which is beyond the scope of this work.

This work considers the techno-economics of small-scale residential heating technologies within a changing energy system. It develops a technology-rich model of a range of small-scale heating systems, and considers their economic performance in scenarios of broader energy system change drawn from a new dispatch model of the electricity system. By bringing these models together new insights can be drawn into the primary factors that impact upon the success of approaches to residential heat decarbonisation.

The primary novel contributions of this study are highlighted as follows. The key contribution is the analysis of individual residential heating systems in the context of electricity system decarbonisation. This is achieved by transferring electricity prices from the power dispatch model described in the previous chapter to an individual residential heating system model described in this chapter. This work incorporates Equivalent Annual Cost (EAC) as the performance index which drives technology selection in contrast to existing works which compare primary energy consumption and emissions. This is done since economic viability is seen to be the most important factor from the consumer's perspective. This analysis also required characterisation of an electricity price regime that is based on long run marginal electricity costs. Hence this work has developed an electricity price regime that incorporates capital costs and annual utilisation, analogous to the cost of power purchase agreement or similar market instruments suitable for low carbon generators.

The work is structured as follows: the next section presents the methodology applied herein to characterise small scale heating and the possible energy systems it could operate within. The results are then presented and discussed, leading to conclusions.

4.2. Methodology

As explained in Section 2.1 this work transfers the electricity prices produced by the power dispatch model to the individual heating system model. This sole link between these two models is a time varying parameter that depends upon the energy mix and the electricity price regime adopted by the electricity grid.

4.2.1. Problem Statement

An overview of the power dispatch model used in this chapter is presented in Table 5.

Table 5 - Problem statement for the power dispatch model Chapter 4

Inputs	Model	Outputs
Demand Profile Renewable Generation Profile Energy Mix Generator Specifications Fuel Price Carbon Price **O & M Price** **Capital Cost** **Annual Utilisation**	Objective: Minimise Cost of Operation Constraints: Load Balance Feasible Operating Envelope	Generator Output Level Electricity Price Profile

The new entries are highlighted in blue. These new entries are required for the electricity price regime based on the Long Run Marginal Cost of electricity. Other elements remain the same.

An overview of the heating system model used in this chapter is presented in Table 6.

Table 6 - Problem statement for the heating system model in Chapter 4

Inputs	Model	Outputs
Electricity price Unit Retail Price Fuel Price Carbon Price Heat Demand Profile Electricity Demand Profile	Objective: Minimise Cost of Operation (includes export revenue for micro CHP)	Energy Balance Operating Cost Export Revenue Equivalent Annual Cost Annual Emissions
	Constraints: Load balance Feasible Operating Envelope Thermal Storage Operation	

The Equivalent Annual Cost is not a direct output of the model. It is calculated using the annualised capital cost, operating cost and export revenue as explained later. Similarly, annual emission is calculated from energy balance by multiplying gas and electricity import/export with their respective emission intensities.

This chapter builds upon the work of Hawkes et al. (Hawkes, Brett, et al., 2009). This chapter extends Hawkes et al. in a number of ways. Most importantly this thesis conducts its analysis in the context of a low carbon future while Hawkes et al. is limited to a present day scenario. To this end, this thesis makes use of a power dispatch model that analyses generator operation and outputs the wholesale price of electricity in a low carbon future. This time varying electricity price is transferred to the heating system model. Another important distinction is that this chapter also includes technologies such as the heat pump and electric heater in addition to micro cogeneration.

4.2.2. Power Dispatch Model

The previous chapter concluded that a high penetration of low carbon sources results in a weak economic signal in terms of wholesale electricity price. Therefore we introduce an alternative electricity price regime to reinforce the revenue stream. Incorporating the capital cost and the utilisation of the generator into the wholesale electricity price reduces the risk faced by individual power producers. This alternative electricity price regime is referred to as the long run electricity price regime and the status quo is referred to as the short run electricity price regime.

All of the Equations from the short run electricity price regime in Chapter 3 are retained in the long run electricity price regime except the objective function. The objective function now includes the annualised capital cost and annual utilisation of different technologies. This is derived from the Average Energy Cost defined by Stoft (Stoft, 2002) which is a function of fixed cost, capacity factor and variable cost as shown in Equation (36):

$$Average\ Energy\ Cost\ = \frac{Fixed\ cost}{Capacity\ factor} + Variable\ cost \tag{36}$$

The long run marginal cost used in this work substitutes the fixed cost with the amortised value of the overnight cost per unit capacity. The variable cost is replaced by the short run marginal cost of electricity. This representation of electricity cost is analogous to what might be expected in a power purchase agreement auction for low carbon sources (Roques, Newbery, & Nuttall, 2008; Salci & Jenkins, 2017).

Since the dispatch of units is dependent on the capacity factor which is in turn dependent on dispatch, straight forward substitution is not possible, a recursive loop is used as explained below.

The cost component related to annualised capital cost divided by capacity factor is called the capital-utilisation factor or CU cost. The renewable components only have a CU cost and do not have other associated costs. The conventional generators have additional components related to fuel, carbon, start-up, operation and maintenance cost. As the loop progresses utilisation of different conventional generators change. The utilisation of renewables remains constant since cost of renewables is still lower than the conventional sources even with the capital-utilisation cost. If the utilisation of a conventional generator increases, its CU cost decreases and thus its likelihood of dispatch increases. As dispatch is non-linear process involving start-up and ramping, the loop continues until the CU costs converge for all technologies. The objective function is shown in Equation (37):

$$Minimize \sum_{j \in J} \sum_{t \in T} \left(c_{j,t}^{CU} + c_{j,t}^{fuel} + c_{j,t}^{carbon} + c_{j,t}^{startup} + c_{j,t}^{O\&M} \right) + c_{wind,t}^{CU} + c_{solar,t}^{CU} \tag{37}$$

Where $c_{j,t}^{CU}$ is the capacity utilisation cost of thermal unit j in period t, $c_{j,t}^{O\&M}$ is the operation and maintenance cost of thermal unit j in period t, $c_{wind,t}^{CU}$ refers to the capacity utilisation cost of wind in period t and $c_{solar,t}^{CU}$ refers to the capacity utilisation cost of solar in period t.

4.2.3. Individual Heating System Model

4.2.3.1. System Description

This model represents the operation of different heating technologies within a household. The different options considered are summarised in Table 7. The interactions between each of these components are shown in Figure 18. The electric heater mentioned here refers to an immersion heater that is meant to evaluate whether variations in the electricity price provide scope for reducing operating cost.

The system is exposed to time varying electricity prices, import is charged at retail price and export attracts revenue at wholesale price. This provides a mechanism to feed information about the supply side to the demand side. Higher export prices are encountered when expensive plants are being dispatched. Distributed generation can support the grid during these periods by exporting electricity. This is a significant development since in the current system distributed generation only attracts a fixed export price irrespective of the time of day. The inputs from the power dispatch model provide the wholesale price. Wholesale prices are uplifted by taxes, fuel duties and policy cost recovery based on data from the UK government (BEIS, 2016b) to calculate retail prices.

Economic performance is measured in terms of Equivalent Annual Cost. This metric consists of annualised capital cost, operating cost and export revenue. Environmental performance is measured in terms of carbon emissions produced during operation. Other environmental factors such as lifecycle emissions and local air quality are not part of this work.

Table 7 - Heating technology options

Case	Heat	Electricity
Reference	Boiler	Grid import
Electric heater	Boiler, Electric heater Thermal Energy Storage	Grid import
Air source heat pump	Heat pump Thermal Energy Storage	Grid import
Micro-CHP	Boiler, Micro-CHP prime mover Thermal Energy Storage	Grid import, Micro-CHP

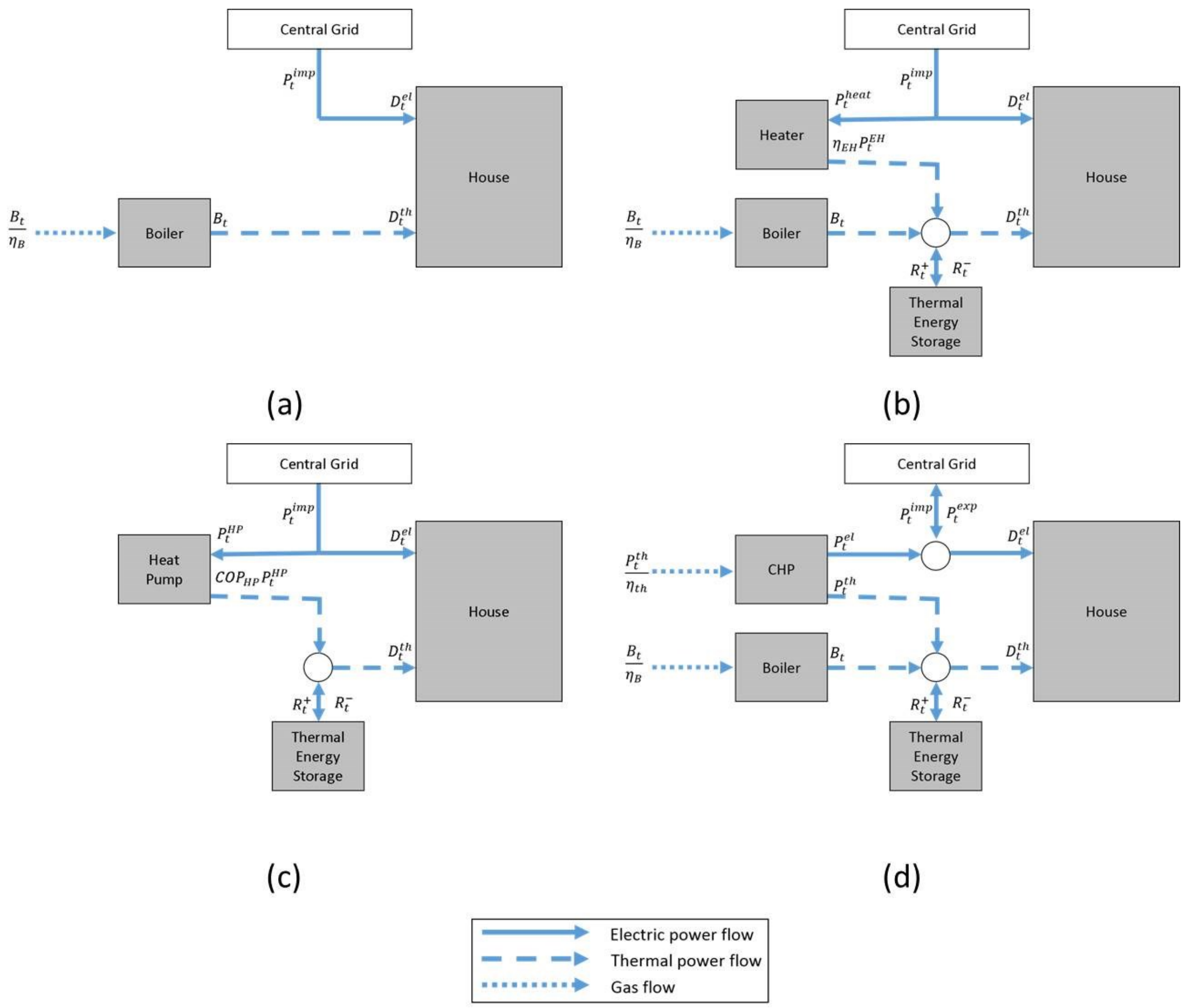

Figure 18 - Heating system schematics (a) Reference (b) Electric heater (c) Air source heat pump (d) Micro-CHP

4.2.3.2. Model Structure

Heating system control is determined by the solution of an optimisation problem. Like the electricity system dispatch model, it is based on a Mixed Integer Linear Program. This is in contrast to the heat/electricity led operation and analytical simulation equations often used in existing literature. There are two factors which make an optimisation approach better suited to the current problem: (1) Time varying nature of electricity prices and (2) presence of thermal energy storage. The optimisation problem is able to calculate the best strategy that will result in the most value to the consumer. This can be through the usage of the thermal energy storage to reduce operational cost or through increase in on-site generation to export electricity during periods of high prices to increase revenue. The optimisation approach is meant to be implemented with feedback about the state of charge of the storage unit and electricity price. The model is applied to four representative days in a year (one for each season). Each day is divided into five minute intervals. The results from each day are weighted appropriately to calculate the annual performance indices used for comparison. Details regarding mathematical modelling of these constraints are presented below.

For the electric heater and heat pump, the objective function only consists of operating costs as shown in Equation (38).

$$\lambda = \sum_{t \in T} (\beta_t) \tag{38}$$

Where λ is the objective function and β_t is the operating cost. For micro-CHP units the objective includes revenue from the export of electricity as shown in Equation (39).

$$\lambda = \sum_{t \in T} (\beta_t - \gamma_t) \tag{39}$$

Where γ_t is the export revenue. Operational costs are the cost of natural gas and electricity imported. The cost of natural gas includes a fuel cost and a carbon cost. For the electric heater this describes consumption of the boiler and the overall electrical demand including heater usage as shown in Equation (40).

$$\beta_t = \left(\frac{B_t}{\eta_B}\right)\left(\alpha_{gas} + \alpha_{CO2}e_{gas}\right) + P_t^{imp}\alpha_t^{imp} \quad (40)$$

Where B_t is the thermal output of the boiler in period t, η_B is the efficiency of the boiler, α_{gas} is the retail price of natural gas, α_{CO2} is the non-traded price of carbon, e_{gas} is the carbon intensity of natural gas, P_t^{imp} is the electricity imported in period t and α_t^{imp} is the price of importing electricity in period t.

For the heat pump, only electricity is consumed as this does not include a boiler as shown in Equation (41).

$$\beta_t = P_t^{imp}\alpha_t^{imp} \quad (41)$$

For the micro-CHP unit, gas is consumed by both the boiler and the micro-CHP unit. Electricity imported is added to cost as shown in Equation (42).

$$\beta_t = \left(\frac{P_t^{th}}{\eta_{th}} + \frac{B_t}{\eta_B}\right)\left(\alpha_{gas} + \alpha_{CO2}e_{gas}\right) + P_t^{imp}\alpha_t^{imp} \quad (42)$$

Where P_t^{th} is the thermal output of the micro cogeneration unit in period t and $\eta_{th}$is its thermal efficiency. Export revenue is the product of electricity exported and the export price of electricity summed over all periods as shown in Equation (43).

$$\gamma_t = P_t^{exp}\alpha_t^{wholesale} \quad (43)$$

Where P_t^{exp} is the electricity exported in period t and $\alpha_t^{wholesale}$ is the wholesale price of electricity in period t. With regard to electrical power balance, generation and import are on the left side of the equation. Demand and export are on the right side of the equation. The components for the electric heater, heat pump and micro-CHP are shown in Equation (44), Equation (45) and Equation (46) respectively.

$$P_t^{imp} = P_t^{EH} + D_t^{el} \tag{44}$$

$$P_t^{imp} = P_t{}^{HP} + D_t^{el} \tag{45}$$

$$P_t^{imp} + P_t^{el} = P_t^{exp} + D_t^{el} \tag{46}$$

Where P_t^{EH} is the electricity consumed by the electric heater in period t, D_t^{el} is the electrical demand in period t, $P_t{}^{HP}$ is the electricity consumed by the heat pump in period t, P_t^{el} is the electricity generated by the micro cogeneration unit in period t and P_t^{exp} is the electricity exported in period t. When considering thermal load balance, heat supplied by installed technology and the natural gas boiler are on the left side of the equation. Demand and storage are on the right side of the equation. The components for the electric heater, heat pump and micro-CHP are shown in Equation (47), Equation (48) and Equation (49) respectively.

$$B_t + \eta_{EH} P_t^{EH} = D_t^{th} + R_t^+ - R_t^- \tag{47}$$

$$COP_{HP} P_t^{HP} = D_t^{th} + R_t^+ - R_t^- \tag{48}$$

$$B_t + P_t^{th} = D_t^{th} + R_t^+ - R_t^- \tag{49}$$

Where η_{EH} is the efficiency of the electric heater, D_t^{th} is thermal demand in period t, R_t^+ is discharge from thermal storage in period t, R_t^- refers to charging of thermal energy storage in period t and COP is the coefficient of performance of the heat pump. The heat to power ratio governs the relation between thermal and electrical power supplied by a micro-CHP unit as shown in Equation (50).

$$P_t^{el} = \eta_{el} \left(\frac{P_t^{th}}{\eta_{th}} \right) \tag{50}$$

Where η_{el} is the electrical efficiency of the micro cogeneration unit. The following equations govern thermal storage operation. Current state of charge is a function of previous state of charge and the charging/discharging level in the current period as shown in Equation (51). The storage unit is not allowed to charge and discharge simultaneously according to Equation (52). Charging and discharging limits are governed by Equation (53) and Equation (54). The state of charge at the beginning of the planning horizon is the same as that seen at the end according to Equation (55). Storage capacity is defined by Equation (56).

$$S_t = S_{t-1} + \eta_{ch} R_t^+ - \frac{R_t^-}{\eta_{disch}} \tag{51}$$

$$\phi_t^+ + \phi_t^- \leq 1 \tag{52}$$

$$0 \leq R_t^+ \leq \overline{S}\phi_t^+ \tag{53}$$

$$0 \leq R_t^- \leq \overline{S}\phi_t^- \tag{54}$$

$$S_1 = S_{T_{end}} \tag{55}$$

$$0 \leq S_t \leq \overline{S} \tag{56}$$

Where S_t is the storage level in the thermal energy storage, η_{ch} is the charging efficiency of thermal energy storage, η_{disch} is the discharging efficiency of thermal energy storage, ϕ_t^+ is the charging mode indicator of thermal energy storage in period t, ϕ_t^- is the discharging mode indicator in period t and $\overline{S}$ is the storage capacity of thermal energy storage. Each of the components: boiler, electric heater, heat pump and micro-CHP have associated capacity limits. These are described by Equations (57) to (60).

$$0 \leq B_t \leq \overline{B} \tag{57}$$

$$0 \leq P_t^{EH} \leq \overline{P^{EH}} \tag{58}$$

$$0 \leq P_t^{HP} \leq \overline{P^{HP}} \tag{59}$$

$$0 \leq P_t^{el} \leq \overline{P^{el}} \tag{60}$$

Where $\overline{B}, \overline{P^{EH}}, \overline{P^{HP}}$ *and* $\overline{P^{el}}$ refer to the maximum capacities of the boiler, electric heater, heat pump and micro cogeneration unit.

4.2.3.3. Performance Indicators

This study focuses on the comparison of economic and environmental performance. Economic performance is measured in terms of the Equivalent Annual Cost (EAC) which is defined as the export revenue subtracted from the sum of annualized capital and operational costs. Revenue and operational costs are weighted according to sample weights of representative days. This is shown in Equation (61) for heating systems other than micro CHP and Equation (62) for micro CHP.

$$\Phi = \Psi \frac{\mathrm{r}}{1 - \frac{1}{(1+r)^L}} + \sum_{k \in K} w_k \left(\sum_{t \in T_h} (\beta_t) \right) \tag{61}$$

$$\Phi = \Psi \frac{\mathrm{r}}{1 - \frac{1}{(1+r)^L}} + \sum_{k \in K} w_k \left(\sum_{t \in T_h} (\beta_t - \gamma_t) \right) \tag{62}$$

Where Φ is the Equivalent Annual Cost, Ψ is the upfront cost of the heating technology, r is the discount rate and w_k is the weight of each sample day k. Environmental performance is measured in terms of annual carbon emissions. This value is also weighted according to sample weights of representative days. Net emission for each sample day is defined as credit received for on-site generation subtracted from the sum of emissions from natural gas consumptions and electricity import. This is shown in Equation (63) for heating systems other than micro CHP and Equation (64) for micro CHP.

$$\mathrm{E} = \sum_{k \in K} w_k \left(\sum_{t \in T_h} \left(e_{gas} \left(\frac{B_t}{\eta_B} \right) + e_{el} P_t^{imp} \right) \right) \tag{63}$$

$$\mathrm{E} = \sum_{k \in K} w_k \left(\sum_{t \in T_h} \left(e_{gas} \left(\frac{B_t}{\eta_B} + \frac{P_t^{th}}{\eta_{th}} \right) + e_{el} P_t^{imp} - e_{el} P_t^{el} \right) \right) \tag{64}$$

Where E is the annual carbon emissions, e_{gas} is the carbon intensity of gas and e_{el} is the carbon intensity of electricity.

4.2.4. Data Used in the Simulations

Capital costs of different generator types are from a tool developed by the UK government (BEIS, 2013a). Lifespan values for generator types are from (Tidball, Bluestein, Rodriguez, & Knoke, 2010). Assumptions in the future electricity system scenario such as energy mix, fuel prices and renewable output are the same as those used in Chapter 3, using the National Grid Gone Green scenario as a basis. The intensity of carbon emissions for electricity generation for the year 2035 is from the same National Grid reference (National Grid, 2015) used in Chapter 3. Natural gas prices are from the UK governments projections for the year 2035 (BEIS, 2016b). Carbon prices are based on the non-traded price of carbon data in the UK government's valuation of energy use and greenhouse gas emissions (BEIS, 2017c). The carbon intensity of natural gas is from a report on greenhouse gas reporting released by the UK government (BEIS, 2016a). The uplift of wholesale price to give retail price is based on projections generated by the UK government (BEIS, 2016b). Capital costs for heating technologies in the year 2035 are within the ranges specified in (Sweett Group for DECC, 2013) and cross-referenced with the UK TIMES model (Daly & Fais, 2014). Technology learning for the fuel cell, Stirling engine and heat pump has been discussed in existing literature (Staffell & Green, 2013; Sweett Group for DECC, 2013; Weiss, Junginger, Patel, & Blok, 2010). As these learning curve forecasts tend to be especially optimistic about reduction in capital cost, this work makes use of realistic estimates used in the UK TIMES model (Daly & Fais, 2014).Further details and individual values are presented in Appendix A.

4.3. Results and Discussion

4.3.1. Power Dispatch Model

4.3.1.1. Comparison of Wholesale Electricity Price Distribution

The dispatch problem calculates which generators are online at various points during the day. This selection is based on long run and short run costs depending on the regime used. The inclusion of capital cost significantly changes the distribution of prices as shown in Figure 19. Mean of prices under the long run regime is around 70 £/MWh and mean under the short run regime is close to 20 £/MWh. The low short run prices are due to a five-fold increase in renewable capacity in the overall electricity grid in the UK. Therefore the amount of zero short run marginal cost power being injected into the grid is considerably larger in the low carbon scenario. The mean electricity price encountered in the UK in the present day is around 50 £/MWh. Hence, a sixty percent decrease in electricity prices weakens the economic case for generators. They will not be able to pay back their capital costs if such low prices were to persist. The long run cost, which is analogous to the price one would expect in low carbon generation power purchase agreement auctions, is arguably a more reflective representation of future electricity prices.

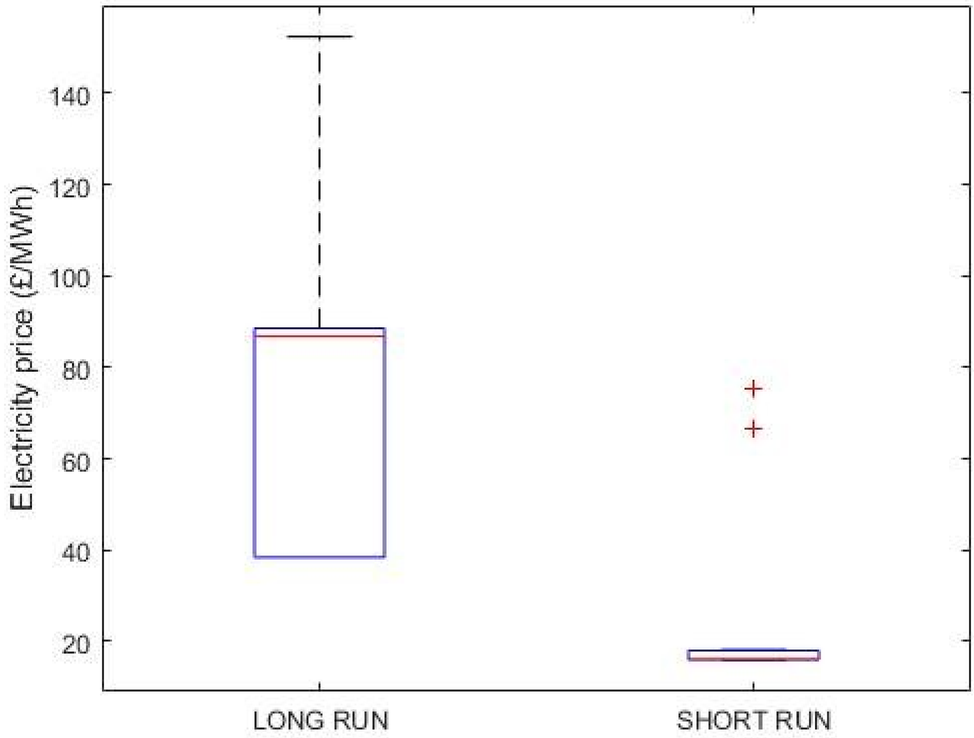

Figure 19 - Comparison of electricity price distribution[4].

4.3.1.2. Analysis of Wholesale Electricity Prices in the Long Run Electricity Price Regime

This section deals with the factors that drive wholesale prices in the long run electricity price regime. It restricts itself to the long run electricity price regime as the short run regime has been discussed in detail in Section 3.3. It should be noted that the overall price is the marginal cost of the most expensive generator online at any point of time. The dispatch of generators is based on long run costs that have an additional term related to the amortised upfront costs and annual utilisation. Thus renewable sources also have an associated cost.

Operation of the long run regime on a spring day is shown in Figure 20(a) and Figure 20(c). There is plenty of sunlight and wind as seen in Figure 20(a). Fossil fuel generators are not necessary except after 6 PM since sunlight dies down in the evening. The operation of nuclear and wind till 7 AM

[4] The top and bottom edges of the blue box are the third and first quartiles of the distribution. The distance between them is the Inter-Quartile Range (IQR). The red line inside the box is the median. The red crosses are outliers, they are points that are either more than 3 × IQR above the third quartile or 3 × IQR below the first quartile. The horizontal black lines are the maximum and minimum values within the 3 × IQR distance specified above.

results in relatively low values of electricity price as seen in Figure 20(c). Injection of solar power increases price towards mid-day. The marginal cost of solar power is larger than wind due to a lower value of capacity factor. A further increase in electricity price is seen beyond 6 PM due to the dispatch of Coal units fitted with Carbon Capture and Storage (CCS). As utilisation of conventional generators decreases significantly in a low carbon future, their marginal cost is larger.

Operation of the long run regime on a winter day is shown in Figure 20(b) and Figure 20(d). There is lesser sunlight but plenty of wind as seen in Figure 20(b). The electricity price increases at 7:30 AM due to the dispatch of two Coal units fitted with Carbon Capture and Storage (CCS) that responded to an increase in demand. They were dispatched since these units have the lowest long run marginal costs after nuclear units. These units remain online and serve demand at various points when renewable output and pumped storage falls short of overall consumption. This results in a higher electricity price between 7:30 AM and 8 PM as seen in Figure 20(d). The relatively higher values of electricity price after these units go offline at 8 PM is due to the associated cost of pumped storage discharge.

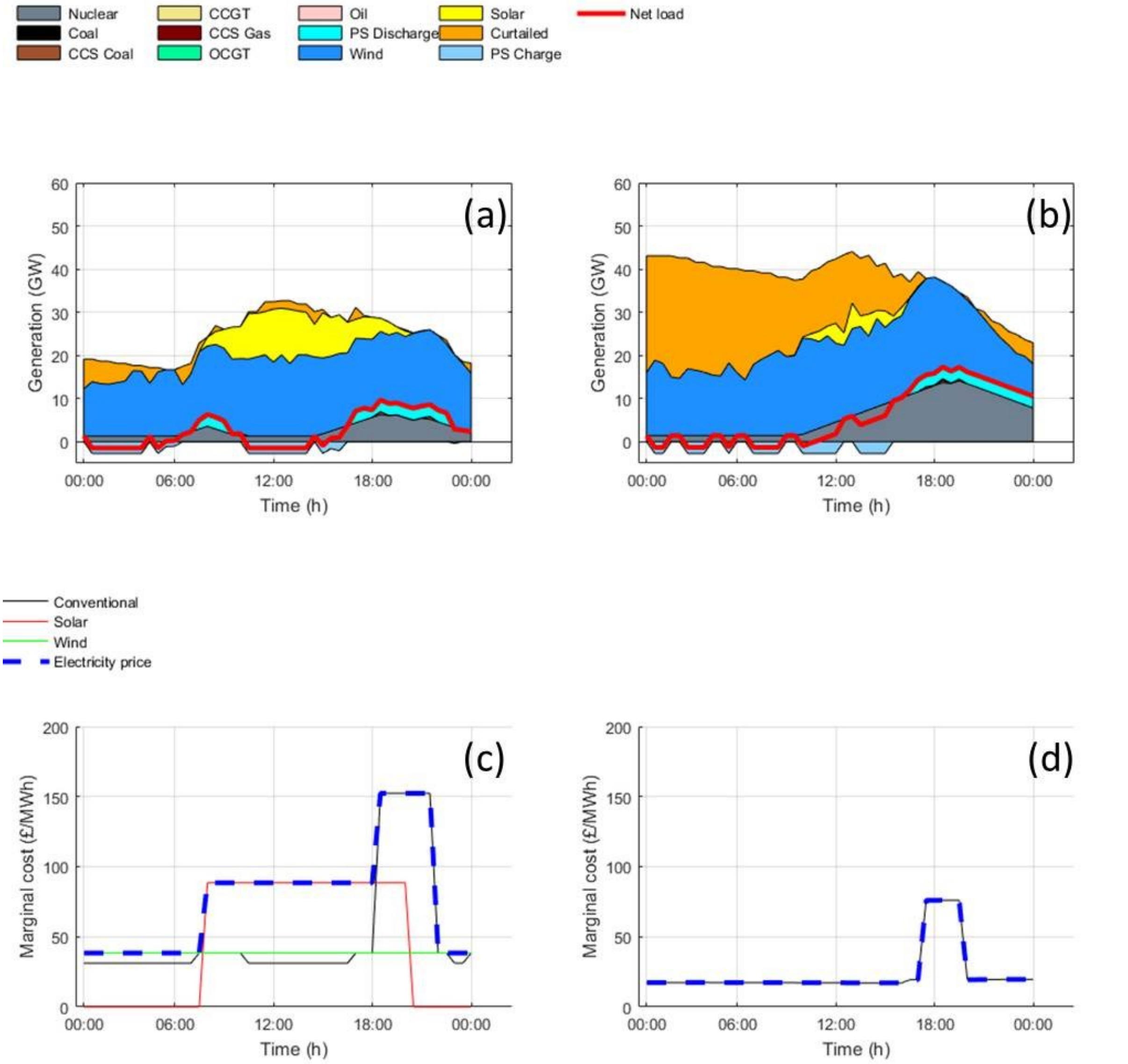

Figure 20 - Analysis of electricity prices in the long run electricity price regime (a) Dispatch on a spring day (b) Dispatch on a winter day (c) Marginal costs on a spring day (d) Marginal costs on a winter day

4.3.2. Performance of Heating Systems

The operation of the heating system is simulated by the optimisation problem described in Section 0. Representative demand profiles for three house sizes: small, medium and large are used. The demand profiles used for this representation are sourced from (Carbon Trust, 2011), and depict four seasons using a highly temporally-resolved diurnal profile for each. Annual values of electric and heat demand for each house are presented in Table 8. Five different heating system options are compared: Boiler, electric heater, air source heat pump, fuel cell micro CHP and Stirling engine micro CHP. All options are compared to incumbent technology in the UK, which is a boiler for providing heat, with electricity from the central grid to serve the electricity demand.

Table 8 - Annual demand values

House	Electricity (kWh)	Heat (kWh)
Small	2601.3	8056.1
Medium	6871.8	12142.8
Large	5938.0	16669.7

4.3.2.1. Equivalent Annual Cost (EAC)

The Equivalent Annual Cost (EAC) for each of the cases is presented in Figure 21 and Figure 22. A technology option is said to be economically viable if its EAC is lower than the baseline case involving the boiler and central grid. Figure 21 shows that there is little difference in EAC under the short run regime. The decrease in annual electricity costs (in comparison to the baseline) in the fuel cell and Stirling engine cases is due to onsite generation. This decrease is seen to be larger with the fuel cell, which is due to its higher utilisation. Higher utilisation leads to more savings, but the savings are still not enough to offset the additional capital expense. None of the options are seen to be viable in the short run regime except the heat pump in the large house. The heat pump is different from the baseline in two aspects: the absence of gas and carbon costs due to reliance on electricity and the inclusion of a thermal storage unit. Every kWh of thermal demand requires 4.5 p for gas and 2.08 p for carbon costs in the baseline case. Serving an equivalent heat demand with the heat pump is related to the retail price of electricity, which is 13.57 p/kWh, divided by the coefficient of performance of the heat pump resulting in 4.52 p/kWh of thermal demand. So the savings increase as the annual heat demand increases and the heat pump is able to offset the capital costs in the case of the large house.

Higher electricity prices in the long run regime in Figure 22 change the outcome. The higher electricity prices push the heat pump EACs to levels higher than the reference case. High electricity prices and future gas prices are conducive for on-site generation. The higher wholesale price in the long run regime also incentivises micro-CHP to export electricity, further lowering the EACs for these technologies. The fuel cell is able to perform better than the Stirling engine since its low heat-to-power ratio allows for higher utilisation, apparent in the higher level of export and lower consumption of grid electricity. Since micro-CHP units are not allowed to discard excess heat production, the low heat to power ratio of the fuel cell allows for more on-site generation while the high heat to power ratio of the Stirling engine limits its performance. None of the options are cost-competitive except the fuel cell in the large house. As with the short run regime, the savings in operational costs of the fuel cell are enough to offset capital costs only with a large value of annual heat demand.

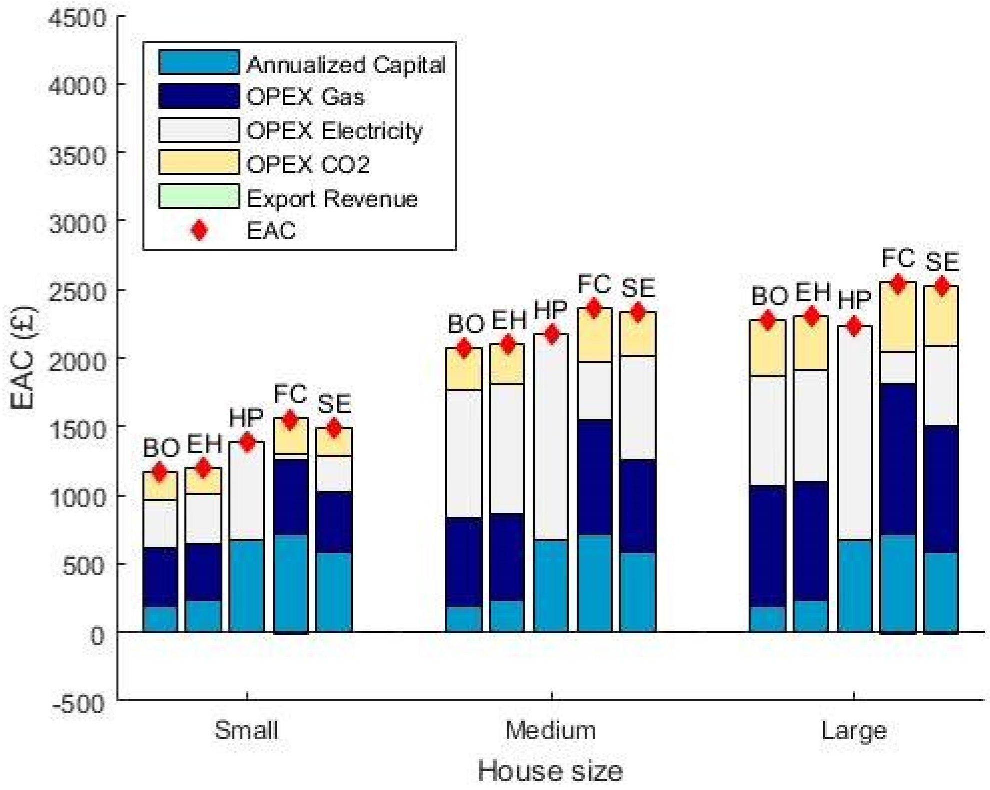

Figure 21 - Equivalent Annual Costs in the short run electricity price regime (BO—Boiler, EH—Electric heater, HP—Heat pump, FC—Fuel cell micro CHP, SE—Stirling engine micro CHP)

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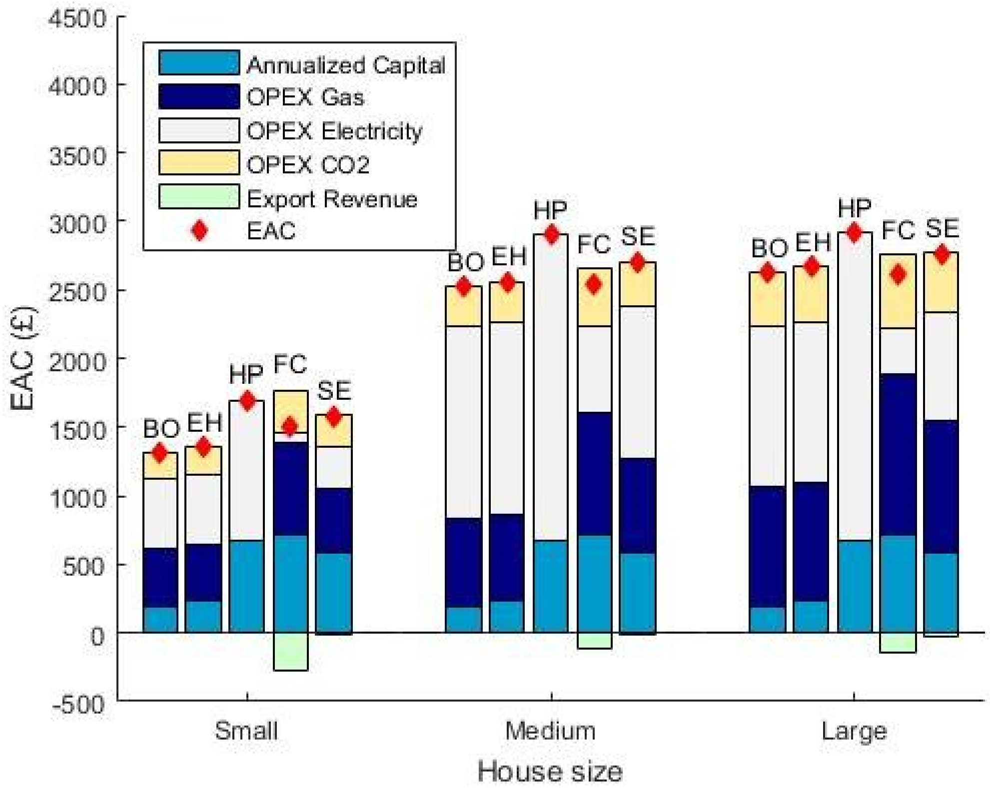

Figure 22 - Equivalent Annual Costs in the long run electricity price regime (BO—Boiler, EH—Electric heater, HP—Heat pump, FC—Fuel cell micro CHP, SE—Stirling engine micro CHP)

It is worth noting that the electric heater is identical to the baseline case. This was included to investigate if there was any scope to make use of variability in electricity prices to buffer energy in the thermal energy storage. The results indicate that electric heater utilisation was not significant.

4.3.2.2. Carbon Emissions

Comparison of the environmental performance of the systems is shown in Figure 23. The heat pump is seen to perform better in both electricity price regimes. This is due to the low carbon intensity associated with electricity grid in the low carbon future scenario. The situation changes when the heating system includes micro CHP units. Co-generation of electricity and heat is more cost effective. But this increases natural gas usage. The net emissions after deducting the amount generated on-site are still higher than the baseline for the fuel cell under both regimes. Emissions from the Stirling engine are slightly lower than the baseline in the short run regime. The economic objective function and the low heat to power ratio of the fuel cell leads to higher onsite generation than the Stirling engine. This leads to higher emissions. As seen before, the electric heater is identical to the baseline due to low heater utilisation.

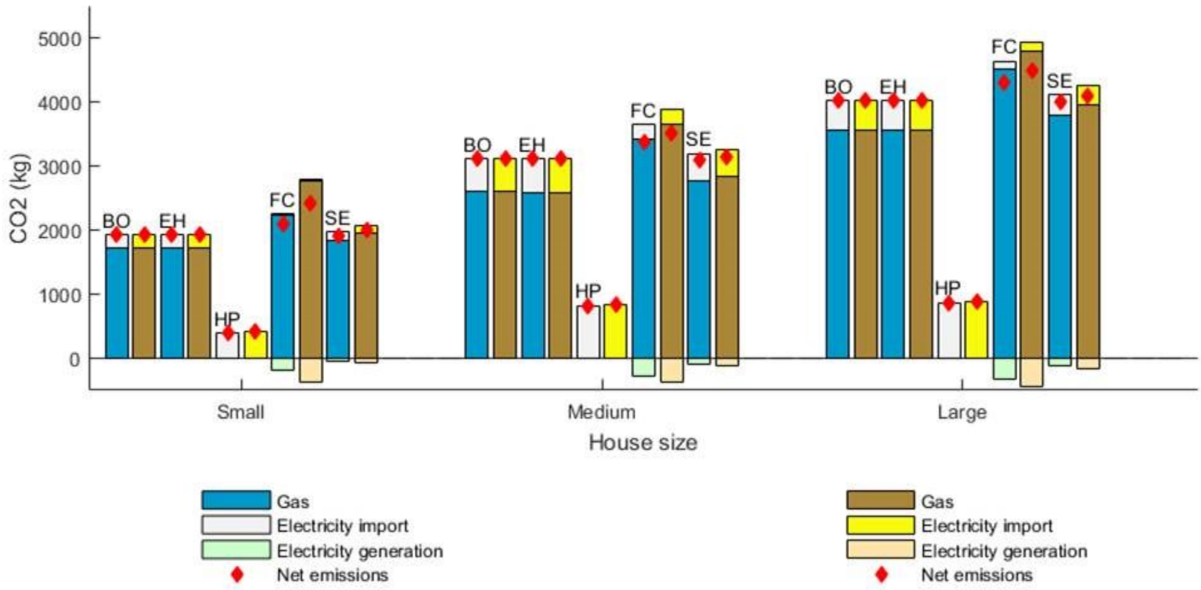

Figure 23 - Annual carbon emissions in the short run and long run electricity price regime (BO—Boiler, EH—Electric heater, HP—Heat pump, FC—Fuel cell micro CHP, SE—Stirling engine micro CHP)

4.3.3. Sensitivity Analysis

The results presented in Section 4.3.2 are closely tied to certain parameters. In this section we study the impact of the most critical parameters which affect the results presented earlier. The two parameters which are most likely to change the environmental and economic performance are carbon intensity of electricity grid and natural gas prices. Analysis of the model equations reveals that a unit change in natural gas price would have the same effect as a corresponding change in the carbon price. Hence, the sensitivities related to natural gas price also apply to corresponding changes in carbon price. Finally this section also discusses the influence of thermodynamic performance criteria on EAC and emissions.

4.3.3.1. Emission Sensitivity

The impact of varying the carbon intensity of electricity grid on annual emissions of a typical medium sized house is shown in Figure 24. It can be seen that the forecast for the carbon intensity of the electricity grid is on the lower end due to the high penetration of low carbon sources.

It can be seen that the solid (short run) and dotted (long run) lines overlap in all cases other than the fuel cell. This is due to the fact that only the fuel cell displays significant change in operation when the electricity price regimes are changed. The boiler and electric heater overlap each other due to low utilisation of the electric heater. The slope of the Stirling engine line is less steep in comparison to the boiler since the net emissions account for electricity export. The heat pump is the best performer until 0.28 $kgCO_2$/kWh beyond which the fuel cell takes over as it gets more credit for on-site generation.

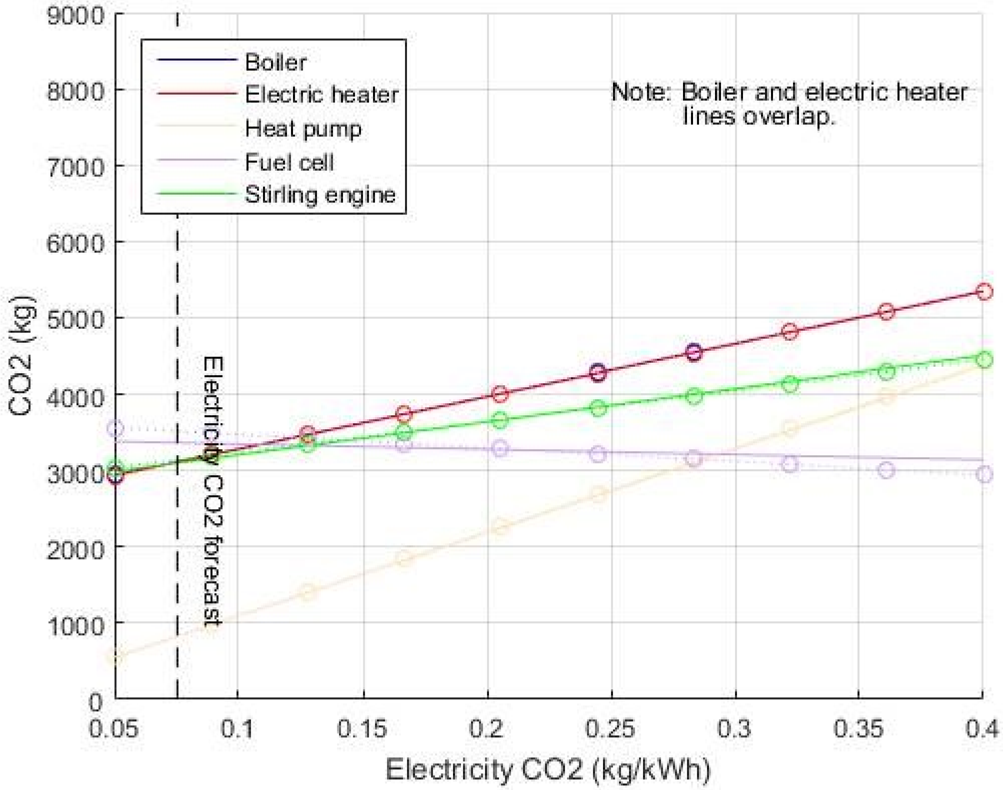

Figure 24 - Emission sensitivity to carbon intensity of the electricity grid in the short run (solid lines) and long run (dotted lines with circle markers) regimes

Another factor that has an indirect impact on annual emission is the price of natural gas. This parameter has an effect on emissions since a change in gas prices results in a change in operation. Results of the sensitivity analysis are shown in Figure 25. As seen earlier, the difference between the regimes is only clear in the fuel cell case. Low utilisation results in overlapping lines for the boiler, electric heater and Stirling engine at higher gas prices. Low gas prices leads to greater on site generation for both the fuel cell and Stirling engine causing an increase in emissions. The fuel cell tends to generate more in the long run regime to export electricity which further increases its emissions. Higher gas prices tend to decrease on-site generation, hence also decreasing emissions.

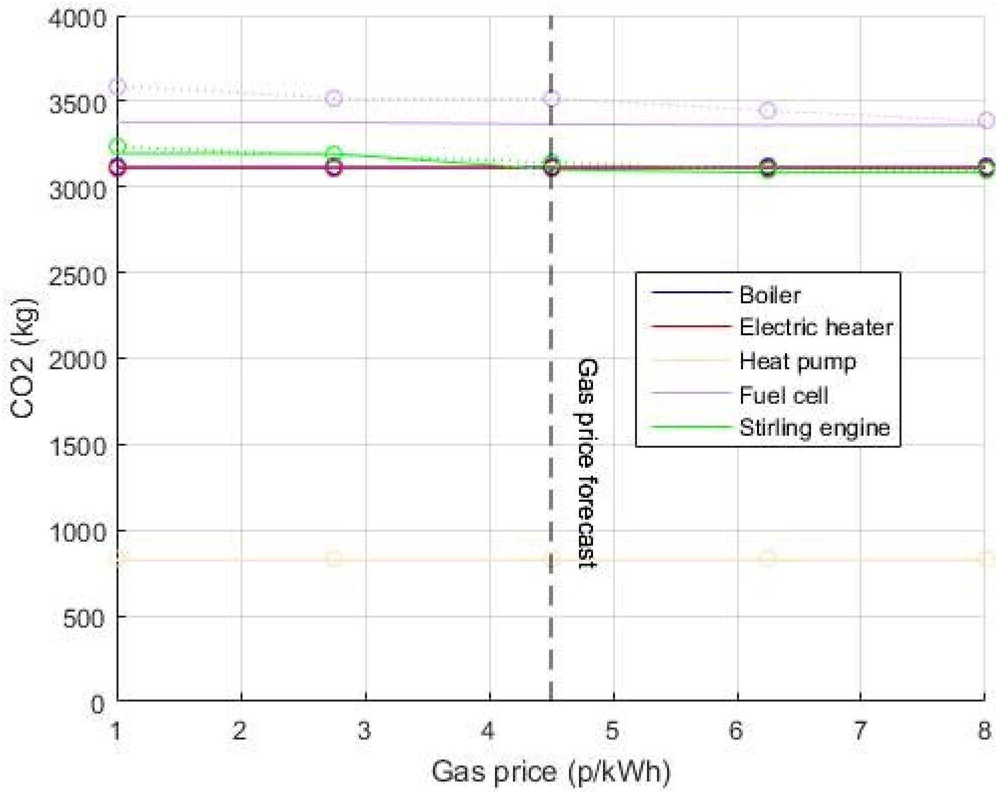

Figure 25 - Emission sensitivity to natural gas price in the short run (solid lines) and long run (dotted lines with circle markers) regimes

4.3.3.2. Equivalent Annual Cost Sensitivity

Natural gas price is very closely tied to the economic performance of the heating system. The changes in EAC under various natural gas prices are shown in Figure 26 and Figure 27. In general, the EACs of all technologies except the heat pump increase with an increase in natural gas prices. This is due to an increase in operational cost for all technologies using natural gas and a decrease in export revenue for micro CHPs. The EACs encountered in the long run regime are higher than those of the corresponding technologies in the short run regime. This can be attributed to higher electricity prices. The Stirling engine and electric heater are not viable for any of the natural gas prices considered in both regimes. The fuel cell is not viable in the short run regime but is found to be useful below a natural gas price of 4.25 p/kWh in the long run regime. This goes to show that export revenue plays a major role in the techno-economics of fuel cells in the long run regime. Export is not as attractive in the short run regime because of lower electricity prices. The inability of the Stirling engine to export much electricity impairs its economic case, even with low natural gas prices in the long run regime. The heat pump operation is not affected by natural gas prices. But its viability is tied to an increase in baseline cost due to an increase in natural gas price. This happens beyond approximately 5.25 p/kWh in the short run electricity price regime and beyond approximately 7.25 p/kWh in the long run electricity price regime.

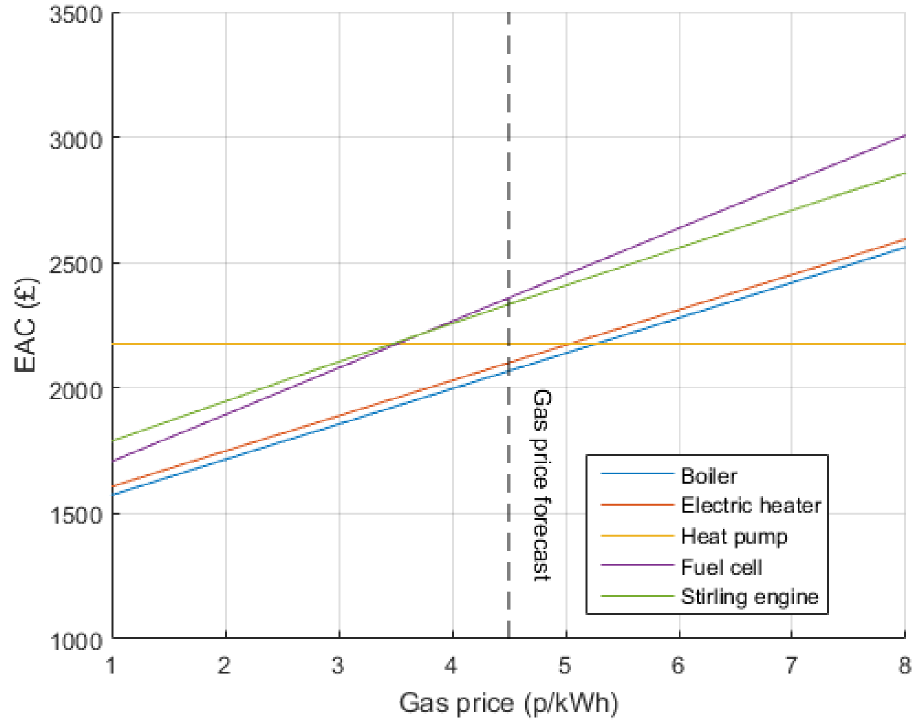

Figure 26 - Equivalent Annual Cost sensitivity to natural gas price in the short run electricity price regime

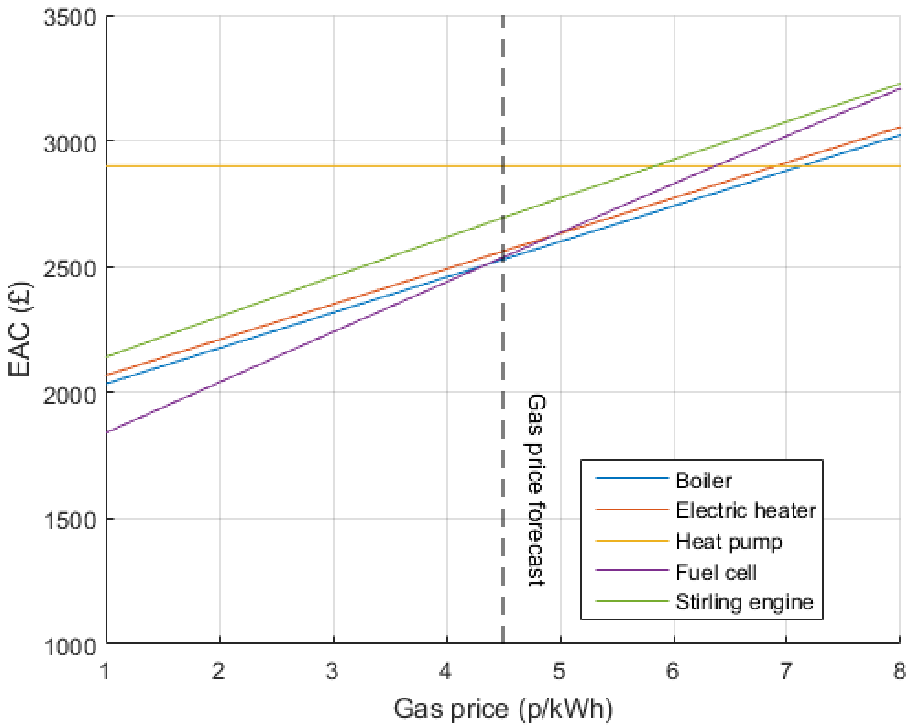

Figure 27 - Equivalent Annual Cost sensitivity to natural gas price in the long run electricity price regime

4.4. Conclusion

In this chapter a novel modelling approach to analysing the impact of power system decarbonisation on the techno-economics of low carbon heating systems has been presented. Since high penetration of low carbon sources in the electricity system is seen to weaken the economic case for investment in generation capacity, an electricity regime based on long run costs instead of short run costs is introduced. In addition to this an optimisation model that determines operating strategies to handle time varying electricity prices and energy balance of thermal energy storage is also discussed. The different sections come together to evaluate technology viability in a future scenario with high penetration of solar, wind and nuclear sources.

The different heating technologies considered are quite similar in terms of annualised cost effectiveness even with optimal operating strategies. Success is likely to be driven by evolution of market conditions and the carbon intensity of the central grid, both of which have been covered in the discussion section. Fuel cells show the most potential under the long run electricity price regime and heat pumps show the most potential under the short run electricity price regime.

The energy requirements of small and medium houses are not sufficient to warrant the installation of new technologies. The savings in operational cost begins to add value for the consumer only when the technologies are installed in dwellings with high values of annual heat demand.

If carbon abatement is the top priority, heat pumps outperform all other options considered in this chapter. However, their economic case is weakened by high capital costs, or by the higher electricity prices observed in the long run electricity pricing regime. Therefore, achieving deep reductions in residential space heating emissions will likely require stronger policy instruments in the medium term; the non-traded carbon price forecast at the time of writing is not sufficient.

Overall it is evident from the results that the best performing heating technology in the future is closely tied to the electricity price regime. The means the electricity market arrangements that determine how price is formed for the consumer will have a significant impact on heating techno-economics. The model described here is a useful tool to evaluate heating systems of the future from the consumer perspective.

5. Dynamic Aspects of Fuel Cell Based Micro Cogeneration

The contents of this chapter are adapted from the following publication:

Vijay, A. and Hawkes, A., 2018. Impact of dynamic aspects on economics of fuel cell based micro co-generation in low carbon futures. Energy, 155, pp.874-886.

5.1. Introduction

Fuel cell based micro co-generation is a promising technology that has several advantages. Their high overall efficiencies allow them to considerably reduce primary energy consumption, and transmission losses via co-locating the system with the demand (Hawkes, Staffell, et al., 2009). They can run on natural gas and thereby capitalize on existing supply network infrastructure. By providing both electricity and heat they help offset the import of electricity and hence reduce associated energy cost. Their high electrical efficiencies and low heat to power ratios also make them well suited for the demand profiles encountered in the domestic sector (Jeremy Cockroft & Kelly, 2006). As large scale uptake of fuel cell based micro co-generation can also help avoid reinforcement of generation capacity, this technology could potentially play a significant role in energy systems of the future (Tapia-Ahumada, Pérez-Arriaga, & Moniz, 2013).

5.2. Novelty and Contributions

5.2.1. Broader Landscape

This chapter inherits two characteristics from Chapter 4 that differentiate it from the broader set of literature on the topic. Fuel cell based micro co-generation systems of the future will have to operate in a significantly different energy system compared to what is seen today. Decarbonisation of the electricity grid is expected to underpin any carbon mitigation strategy that is designed to check the rise in global temperature (R. Kannan, 2009). Examples of studies analysing the intersection between broader energy systems and the supply of heat can be found in (Chiodi et al., 2013; D. Henning, 1997; Ramachandran Kannan & Strachan, 2009; Merkel, Fehrenbach, McKenna, & Fichtner, 2014). Such tools view energy systems from a macro level perspective and hence necessarily involve aggregated representations of regional, national or global participants (S Pfenninger et al., 2014). Information on the economics and operation of individual consumers is lost in such studies which use coarse grained representations. Hence more detailed representations of the end user are required to assess the solutions provided by emerging technologies. Even when individual representations are used as seen in (Jeremy Cockroft & Kelly, 2006; Dorer & Weber, 2009), the discussion of future scenarios is limited to the change in carbon intensity of electricity generation. Our work adds to these by using a detailed power dispatch model to simulate generator operation and market prices in the future scenario.

We have shown in Chapter 3 that decarbonisation through an increase in renewable and nuclear capacity will result in significantly lower wholesale electricity prices in the future. Such weak revenue streams are bound to make it difficult for power plants to break even. In Chapter 4 we introduce a solution that mitigates this risk is the use of an electricity price regime that made use of the long run marginal cost of generation instead of the short run marginal cost regime which is common in today's systems. The long run electricity price regime incorporates capital cost and utilisation into a fixed power purchase agreement. We have also discussed the impact of a long run electricity price regime on the economics of residential heating systems in Chapter 4. The results revealed that fuel cells show the most potential under the long run electricity price regime. This work extends the work in Chapter 4 by assessing the effect of dynamic characteristics on the economics of fuel cell based micro co-generation under the long run electricity price regime.

5.2.2. Specific to this Chapter

This chapter expands upon the previous chapter through explicit characterisation of dynamic aspects of fuel cell based micro co-generation systems, namely; start-up cost, ramping limit, minimum up time, minimum down time and turn down ratio. These parameters are important since fuel cell micro co-generation systems require a multitude of sub systems to function in tandem: the fuel processor, the fuel reformer, the stack, power electronics, actuators, control loops etc. (Hawkes, Staffell, et al., 2009). The operation of each sub systems has implications in terms of performance of the overall unit. For example, since the fuel cell is likely to have more thermal mass than conventional heating systems it is likely to incur a greater energy cost while warming up or starting (Hawkes, Brett, et al., 2009). The dynamics of the fuel processor, reformer and balance of plant determine how quickly the micro co-generation unit can modulate output and hence influence the ramping limit (Bhattacharyya & Rengaswamy, 2009). Thermal characteristics such as minimum stack temperature and thermal cycling affect parameters such as turn down ratio, minimum up time and minimum down time (Hawkes, Brett, & Brandon, 2011). Therefore, the model described in this work can help identify which aspects will improve the economic performance of fuel cell based micro co-generation.

By making use of a sensitivity analysis that varies design parameters, this chapter is able to provide guidelines regarding which specifications affect performance the most. This type of optimisation is different from what is seen in existing literature as discussed in Section 2.3.3. While a lot of effort has been put into the analysis of existing technologies, the literature does not discuss the concept of making use of existing tools to feed information back to the design process to establish future priorities.

The chapter is structured as follows: The next section presents the methodology applied herein to characterise fuel cell based micro co-generation and the possible energy systems it could operate within. This is followed by results and discussion, leading to conclusions.

5.3. Methodology

5.3.1. Problem Statement

An overview of the heating system model used in this chapter is presented in Table 5.

Table 9 - Problem statement for the heating system model in Chapter 4

Inputs	Model	Outputs
Electricity price Unit Retail Price Fuel Price Carbon Price Heat Demand Profile Electricity Demand Profile **Start-up Cost** **Ramping Limit** **Minimum Up/Down Time** **Turndown Ratio**	Objective: Minimise Cost of Operation (includes export revenue) Constraints: Load balance Feasible Operating Envelope Thermal Storage Operation	Energy Balance Operating Cost Export Revenue Equivalent Annual Cost Annual Emissions

The new entries which were not part of the previous chapter are highlighted in blue.

This chapter builds upon the previous chapter by incorporating a detailed treatment of the dynamic aspects of fuel cells. The new constraints included serve as mathematical abstractions of dynamics that are likely to be encountered in fuel cells of the future.

5.3.2. Model Overview

This chapter takes the outputs of a macro national level electricity system model and passes them on to a micro level individual consumer model. The macro level model simulates power dispatch of all generators in a power grid and the micro level model simulates the heating system in an individual household. Detailed descriptions of the power dispatch model and electricity price regimes have been covered in previous chapters.

It is worth noting that this work intentionally makes use of a generic fuel cell description. Particular focus is on characterising the impact of inter-temporal specifications which can be the focus of future research on fuel cell technologies. The data ranges used in the sensitivity studies have purposefully been kept large enough to encompass both high temperature and low temperature fuel cells. The following sections will focus on the consumer side model which highlights the contributions of this chapter.

5.3.3. Individual Heating System Description

This model represents the operation of a fuel cell based micro co-generation within an individual household. The house is also equipped with a natural gas boiler, a thermal energy storage tank and a connection to the central grid. The system is exposed to time varying electricity prices, import is charged at retail price and export attracts revenue at wholesale price. The inputs from the power dispatch model provide the wholesale price. Wholesale prices are uplifted by taxes, fuel duties and policy cost recovery based on data from the UK government (BEIS, 2016b) to calculate retail prices.

5.3.4. Mathematical Model

The model makes use of two control strategies: heat led and optimisation based. Heat led control does not require an iterative solver. It simply follows the heat load by dispatching the micro cogeneration unit first and then using the auxiliary boiler to supply the rest. Any excess electricity generated is exported back to the grid. The optimisation based model is a mixed integer linear program. It is applied to a set of representative days in a year. The representative day selection algorithm is presented in Appendix B. Each day is divided into five minute intervals. The results from each day are weighted approximately equally to calculate the annual performance indices used for comparison.

It is worth noting that this approach intentionally adopts a generic and technology agnostic approach to describing the fuel cell based cogeneration unit. Although the component-wise operation may vary, their dynamics can be captured by using mathematical abstractions. Dynamic characteristics are chosen such they are capable of representing the operation and interactions without going into individual component level detail. This applies to different fuel cell technologies, using different electrolytes, catalysts, reformers, fuel processors etc. The same applies to different balance of plant equipment such as power electronics, actuators, control loops etc.

This model is meant to represent future technologies. They describe characteristic of fuel cell based micro cogeneration units that have not been developed yet. For this reason, we do not compare the chosen parameters with existing technologies. Validation is outside the scope of the current set of objectives. But this does not discount the ability of optimisation problems to represent fuel cell based micro cogeneration units. Several references have used mixed integer linear programs for existing systems as discussed in Section **2.3.3**.

As explained earlier, this chapter improves upon the model in Chapter 4 by accounting for dynamic characteristics of fuel cells that could potentially affect their economic case in low carbon futures. All of these parameters fall under the feasible operating envelope category. They have been summarised in *Table 10*.

Table 10 - Dynamic parameters

Parameter	Description	Physical Relevance
Turn down ratio	The ratio between the minimum and maximum output of the fuel cell micro co-generation unit.	Minimum stack temperature
Minimum up time	The minimum amount of time for which the micro co-generation unit need to remain	Prevention of rapid cycling;

	online once it has been activated.	
Minimum down time	The minimum amount of time for which the micro co-generation unit has to remain offline once it has been shut down.	Prevention of rapid cycling; Cool down period
Ramping limit	The limit on the rate at which the output of the micro co-generation unit can be modulated.	Interactions between equipment; Functioning within safe operating envelope
Cold start-up	The energy cost of starting up the micro co-generation unit when it has been allowed to cool down when offline.	Pre-heating of stack, fuel and air; operation of blowers
Hot start-up	The energy cost of keeping the micro co-generation unit on standby mode when offline.	Maintenance of stack, fuel and air temperature

Details regarding mathematical modelling of these constraints are presented below. Most of the equations from the previous chapter are retained in this model. The changes are presented below. When using the cold start-up method a fixed cost is incurred each time the micro co-generation unit is started up. The operating cost is modified as shown in Equation (65).

$$\beta_t = \left(\frac{P_t^{th}}{\eta_{th}} + \frac{B_t}{\eta_B}\right)\left(\alpha_{gas} + \alpha_{CO2}e_{gas}\right) + P_t^{imp}\alpha_t^{imp} + \alpha_{SUC}\phi_t^{SU} \tag{65}$$

Where P_t^{th} is the thermal output of the micro cogeneration unit in period t, $\eta_{th}$is its thermal efficiency, B_t is the thermal output of the boiler in period t, η_B is the efficiency of the boiler, α_{gas} is the retail price of natural gas, α_{CO2} is the non-traded price of carbon, e_{gas} is the carbon intensity of natural gas, P_t^{imp} is the electricity imported in period t, α_t^{imp} is the price of importing electricity in period t, α_{SUC} is the cold start-up cost and ϕ_t^{SU} is the start-up indicator. When using hot start-up a fixed cost is incurred whenever the micro co-generation unit is not active as shown in Equation (66).

$$\beta_t = \left(\frac{P_t^{th}}{\eta_{th}} + \frac{B_t}{\eta_B}\right)\left(\alpha_{gas} + \alpha_{CO2}e_{gas}\right) + P_t^{imp}\alpha_t^{imp} + \alpha_{SUH}\left(1 - \phi_t^{A}\right) \tag{66}$$

Where α_{SUH} is the hot start-up cost. Start-up and shut down indicators are a function of whether the state of the micro co-generation unit has changed in consecutive time periods as shown in Equation (67).

$$\phi_t^{SU} - \phi_t^{SD} = \phi_t^A - \phi_{t-1}^A \tag{67}$$

Where ϕ_t^{SD} is the shutdown indicator and ϕ_t^A is the active or on/off indicator of the micro cogeneration unit. The ramping limit is a bound on the difference between the outputs in consecutive time periods. It applies to both upward and downward directions as shown in Equation (68) and Equation (69).

$$P_t^{el} - P_{t-1}^{el} \leq \delta_{rmp} \tag{68}$$

$$P_{t-1}^{el} - P_t^{el} \leq \delta_{rmp} \tag{69}$$

Where δ_{rmp} is the ramping limit. The operating limits on on-site generation are modified to include the active state indicator of the micro cogeneration unit as shown in Equation (70).

$$\delta_{tdr}\overline{P^{el}} \leq P_t^{el} \leq \overline{P^{el}}\phi_t^A \tag{70}$$

Where δ_{tdr} is the turndown ratio and $\overline{P^{el}}$ is the maximum capacity of the micro cogeneration unit. Equation (71) enforces the minimum down time constraint for all consecutive sets of periods of length δ_{mdt}. Equation (72) makes sure that if the unit is shut down in the last $\delta_{mdt} - 1$ periods it will remain offline until the end of the planning horizon.

$$\sum_{k=t}^{t+\delta_{mdt}-1} \left(1 - \phi_k^A\right) \geq \delta_{mdt}\phi_t^{SD} \quad \forall t = 1 \cdots T_{end} - \delta_{mdt} + 1 \tag{71}$$

$$\sum_{k=t}^{T_{end}} \left(1 - \phi_k^A - \phi_t^{SD}\right) \geq 0 \quad \forall t = T_{end} - \delta_{mdt} + 2 \cdots T_{end} \tag{72}$$

Equation (73) enforces the minimum up time constraint for all consecutive sets of periods of length δ_{mut}. Equation (74) makes sure that if the unit is started up in the last $\delta_{mut} - 1$ periods it will remain online until the end of the planning horizon.

$$\sum_{k=t}^{t+\delta_{mut}-1} \left(\phi_k^A\right) \geq \delta_{mut}\phi_t^{SU} \quad \forall t = 1 \cdots T_{end} - \delta_{mut} + 1 \tag{73}$$

$$\sum_{k=t}^{T_{end}} \left(\phi_k^A - \phi_t^{SU}\right) \geq 0 \quad \forall t = T_{end} - \delta_{mut} + 2 \cdots T_{end} \tag{74}$$

5.4. Results and Discussion

This chapter has prioritized the analysis of some parameters over others. Start-up is seen to be critical for consumers and designers alike. Hence, analyses of sensitivity to cold and hot start-ups are performed for all cases considered. In order to limit the number of parameters analysed to a manageable value, we include certain modifications. Firstly, minimum up time is equal to minimum down time. And second, we do not vary the values of parameters which have zero impact on economics when incorporated separately into a particular control strategy.

5.4.1. Identification of Significant Parameters

We incorporate each of the following dynamic parameters into the simulation separately: turn down ratio, minimum up/down time and ramping limit. These parameters are varied between their respective maximum and minimum values which are summarised in *Table 11*. These ranges are based on nominal values from (Hawkes, Staffell, et al., 2009).

Table 11 - Ranges of sensitivity values for each of the dynamic parameters. Note: Nominal values were taken from (Hawkes, Staffell, et al., 2009).

Parameter	Units	Nominal	Minimum	Maximum

Turn down ratio	-	0.2	0.2	0.5
Minimum up/down time	H	1	0.5	4
Ramping limit	W/5min	250-1000	100	1000

The range of the Equivalent Annual Cost values obtained for each parameter is shown in Figure 28. The aim is to identify the most important parameters for analysis of the heat led and optimisation based control strategies. The range of values associated with various values of turn down ratio and minimum up/down times is zero for heat led and optimisation based control strategies respectively. This implies that these parameters do not affect operation. Hence turn down ratio and minimum up/down times are left out of the analysis of heat led and optimisation based control strategies respectively.

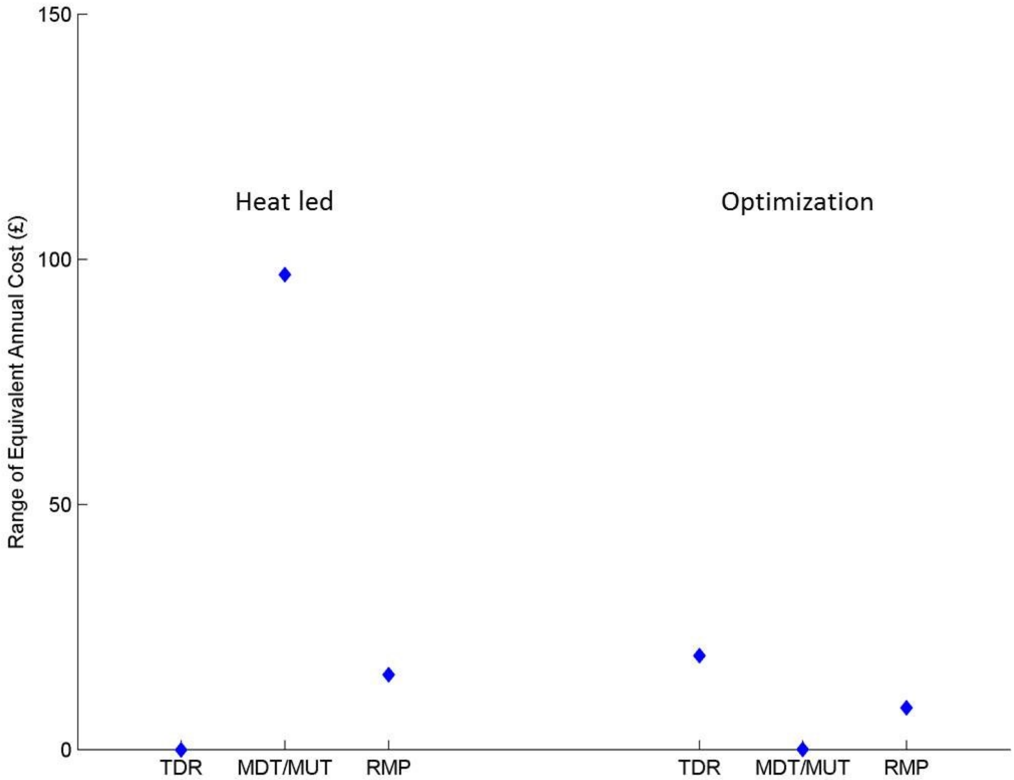

Figure 28 – Range of Equivalent Annual Costs for each dynamic parameter in the initial simulation (TDR – Turn down ratio, MDT – Minimum down time, MUT – Minimum up time and RMP – Ramping limit)

5.4.2. Analysis of Heat Led Control

Let us first analyse the physical phenomena that drive performance. Since it is not feasible to present all of the sensitivity data points, we focus on the extremes. The best case scenario involves the lowest minimum up/down time and the highest ramping limit. This is because a high ramping limit allows the system to react to changes in demand most effectively. And a small minimum up/down time means that the system can shut down and start-up without any constraints that force it to do otherwise. Hence, it follows that the worst case scenario involves the highest minimum up/down time and the lowest ramping limit.

Electrical and thermal power balances are presented in Figure 29. This figure shows how each subsystem is operated to satisfy local demand. The operating principle is simple: follow heat demand by using cogeneration first and the auxiliary boiler next. Export excess and import any deficit in electricity. The effect of dynamic parameters can be seen by comparing the best and the worst case. In Figure 29(b) the system is more reactive and has the flexibility to follow demand. The cogeneration system is able to immediately operate at rated capacity around 4 AM when heat demand increases. This is not the case in Figure 29(d) where the system has to wait until 5 AM to reach rated capacity. The minimum up/down time also affects operation. When the minimum down time value is only half an hour in the best case scenario, the system is able to shut down around 10 AM and start up at noon when demand reappears as seen in Figure 29(b). But in the worst case the system is not able to start generation until 2 PM as seen Figure 29(d). Minimum up time comes into play around 4:30 PM in Figure 29(d) When the system is not able to shut down even through there is no local heat demand. It is worth noting that it is able to reach a low value of output only around 4:30 PM due to a low ramping limit that restrains the cogeneration unit.

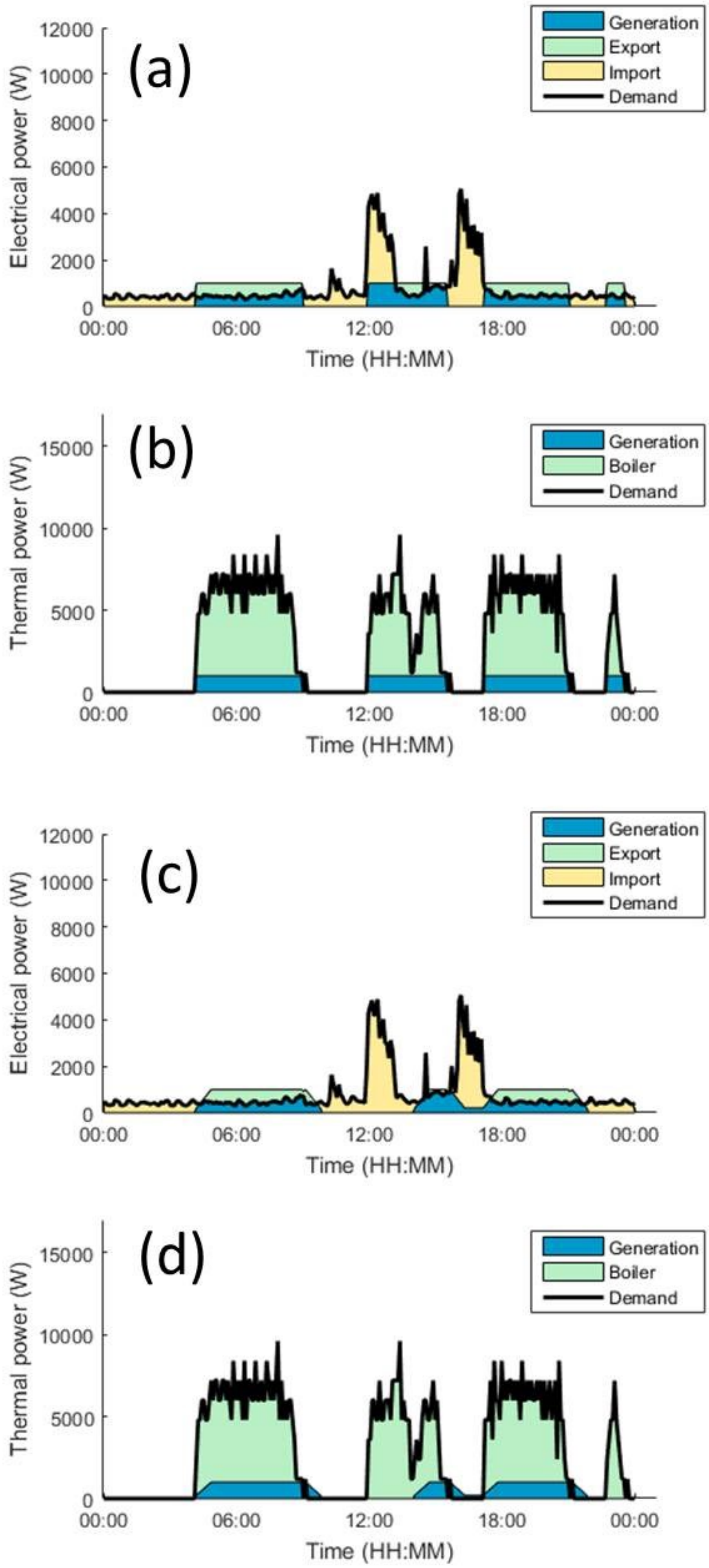

Figure 29 - Physical phenomena that drive performance. Best case: (a) and (b). Worst case: (c) and (d).

The heat led operating strategy does not depend on the start-up method. Hence, the EAC without start-up cost values are identical for the hot and cold start-up methods. The variation of EAC without start up is shown in Figure 30. Minimum up/down time has a stronger effect on performance than the ramping limit. This can be seen by the change in colour of the contour plot from half an hour to four hours. The EAC increases by eighty pounds within the sensitivity range investigated for minimum up/down time. The most important implication of these results is that with a heat led strategy the unit is never economically viable in the sensitivity range considered. This can be seen from the fact that in even without start-up costs, the EAC value is always above the boiler baseline which is £ 2630. As discussed in Section 2.3.3.1, the main drawback of this approach is inefficiency. Hence if the system is operated in heat led mode, it does not justify the investment made in this technology.

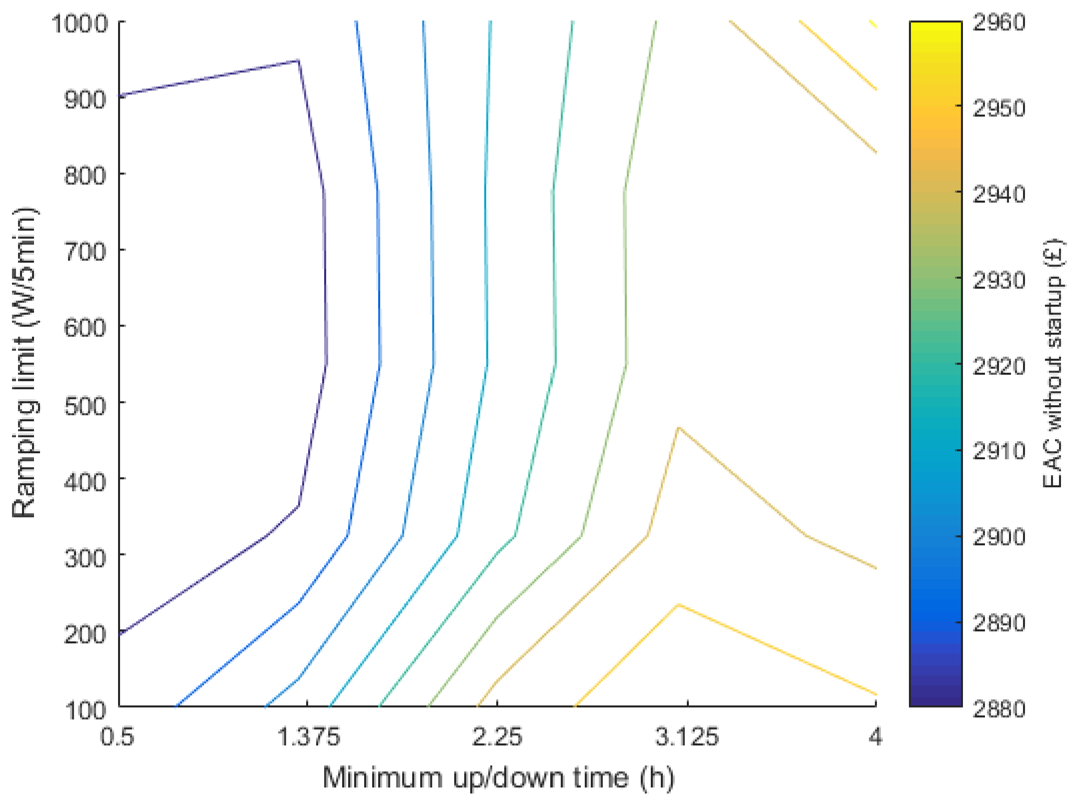

Figure 30 - Variation of EAC without start-up cost under heat lead control

5.4.3. Analysis of Optimisation Based Control

Let us start by considering the EAC without start-up. Hot and cold values were identical for the heat led control strategy because the operating strategy is independent of start-up cost. We perform the same exercise for the optimisation based control strategies as any differences will quickly rule out identical strategies. Table 12 shows the absolute values of EAC without start-up and Table 13 shows the difference between the hot and cold start-up. It can be seen from Table 13 that the difference is less than one-thousandth of the absolute value. This means that the economics are similar but it remains to be seen if the operating strategies are close to each other as well. To evaluate this, we compared the difference between dispatch strategies of the micro co-generation unit.

Table 12 - EAC without start-up (£)

		Turn Down Ratio				
	Value	0.2	0.275	035	0.425	0.5
Ramping Limit (W/5min)	100	3147.2	3147.2	3147.2	3147.2	3147.2
	325	2612.7	2612.9	3147.2	3147.2	3147.2
	550	2611.9	2612.2	2614.6	2622.4	2633.1
	775	2611.9	2612.1	2614.5	2622.4	2633.1
	1000	2611.9	2612.1	2614.5	2622.4	2633.1

Table 13 - Difference between hot and cold start - EAC without start-up (£)

		Turn Down Ratio				
	Value	0.2	0.275	035	0.425	0.5
Ramping Limit (W/5min)	100	0.0	0.0	0.0	0.0	0.0
	325	0.0	0.0	0.0	0.0	0.0
	550	0.0	0.0	0.0	-0.3	-1.6
	775	0.0	0.0	0.0	-0.2	-1.6
	1000	0.0	0.0	0.0	-0.2	-1.6

To ascertain whether they are identical we need to compare the hot and cold strategies first and then compare the difference in operating strategies for various start-up sensitivity values for both hot and cold start-up approaches. The results are summarised in Table 14. Individual dispatch values for the micro co-generation unit are deemed to be identical if the difference between them is less than
10^{-6} W. Nominal values of 0.2 kW for hot standby power and 1 kWh for cold start-up energy cost are from (Sicre, Bühring, & Platzer, 2005) and (Staffell, 2010) respectively.

Table 14 - Comparison of optimisation based operating strategies

Comparison	Percentage of identical elements
Hot standby power (0.2 kW) Vs Cold start-up cost (1 kWh)	98.5
Hot standby power (0.2 kW) Vs Hot standby power (0.3 kW)	99.6
Hot standby power (0.2 kW) Vs Hot standby power (0.4 kW)	99.5
Hot standby power (0.2 kW) Vs Hot standby power (0.5 kW)	99.4
Hot standby power (0.2 kW) Vs Hot standby power (0.6 kW)	99.4
Cold start-up cost (1 kWh) Vs Cold start-up cost (1.5 kWh)	99.8
Cold start-up cost (1 kWh) Vs Cold start-up cost (2 kWh)	99.7
Cold start-up cost (1 kWh) Vs Cold start-up cost (2.5 kWh)	99.7
Cold start-up cost (1 kWh) Vs Cold start-up cost (3 kWh)	99.7

An overwhelming fraction of non-zero dispatch values are identical. This implies that the dispatch optimisation based control strategy is also independent of the type of start-up method used and the magnitude of the start-up cost specified. Hence we proceed to analyse the difference in operating strategies when there is a difference in turn down ratio and ramping limit. This analysis also presents the difference in physical phenomena.

Optimisation cannot make use of the extremes in sensitivity data as seen in the previous section. This can be explained by analysing the cycling patterns in Table 15 and Table 16. They present the number of starts and the percentage of time spent in hot standby mode. It can be seen that the cogeneration unit is not switched on when subjected to certain combinations. This is evident from the number of starts falling to zero and the portion of time spent in hot standby mode goes up to one hundred per cent. One of these combinations is the worst case scenario with the lowest ramping limit and the highest turn down ratio. In these cases the optimisation problem chooses to stick to the boiler and grid electricity since switching on the cogeneration unit is more expensive. Hence the best and worst combinations in which the cogeneration unit is operational are (0.2 turn down ratio, 1000 W/5min ramping limit) and (0.5 turn down ratio, 550 W/5min ramping limit) respectively.

Table 15 - Cold start cycling pattern - Number of starts

		Turn Down Ratio				
	Value	0.2	0.275	035	0.425	0.5
Ramping Limit (W/5min)	100	0	0	0	0	0
	325	365	365	0	0	0
	550	365	365	365	365	365
	775	365	365	365	365	365
	1000	365	365	365	365	365

Table 16 - Hot start cycling pattern - Percentage of time spent in hot standby mode

		Turn Down Ratio				
	Value	0.2	0.275	035	0.425	0.5
Ramping Limit (W/5min)	100	100.00	100.00	100.00	100.00	100.00
	325	5.54	5.54	100.00	100.00	100.00
	550	5.54	5.54	5.54	7.02	8.75
	775	5.54	5.54	5.54	7.10	8.75
	1000	5.54	5.54	5.54	7.10	8.75

Physical phenomena in the two cases considered are shown in Figure 31. Inspection of Figure 31(b) and Figure 31(f) shows that the output of the cogeneration system able to track load changes better between midnight and 8 AM, but the worst case chooses a constant output level due to the low ramping limit and high turn down ratio. The output is increased to maximum capacity between 8 AM and 9 PM in both cases due to high electricity prices. When the difference between rated capacity and on-site load is positive electricity is exported to the grid. Thermal phenomena for the best case are shown in Figure 31(c) and Figure 31(d). The respective counterparts for the worst case are shown in Figure 31 (g) and Figure 31(h). Strategic planning allows the system to store up energy when there is no heat demand and discharge when heat demand increases. Hence the presence of thermal storage decouples the heat supply from demand to a certain extent. As the thermal output is directly linked to electrical output, the shapes seen Figure 31(c) are a consequence of those seen in Figure 31(b). The variation in output is not as clear in Figure 31(c) as the scale of heat demand is larger in comparison to the output of the cogeneration unit. Similarly in the worst case, thermal output is dependent on electrical output as seen in Figure 31(f) to Figure 31(h). Thermal storage is charged three times in both cases, between 7 AM and 10:30 AM, between 11:30 AM and 2 PM and between 7:30 Pm and 9 PM as seen in Figure 31(d) and Figure 31(h).

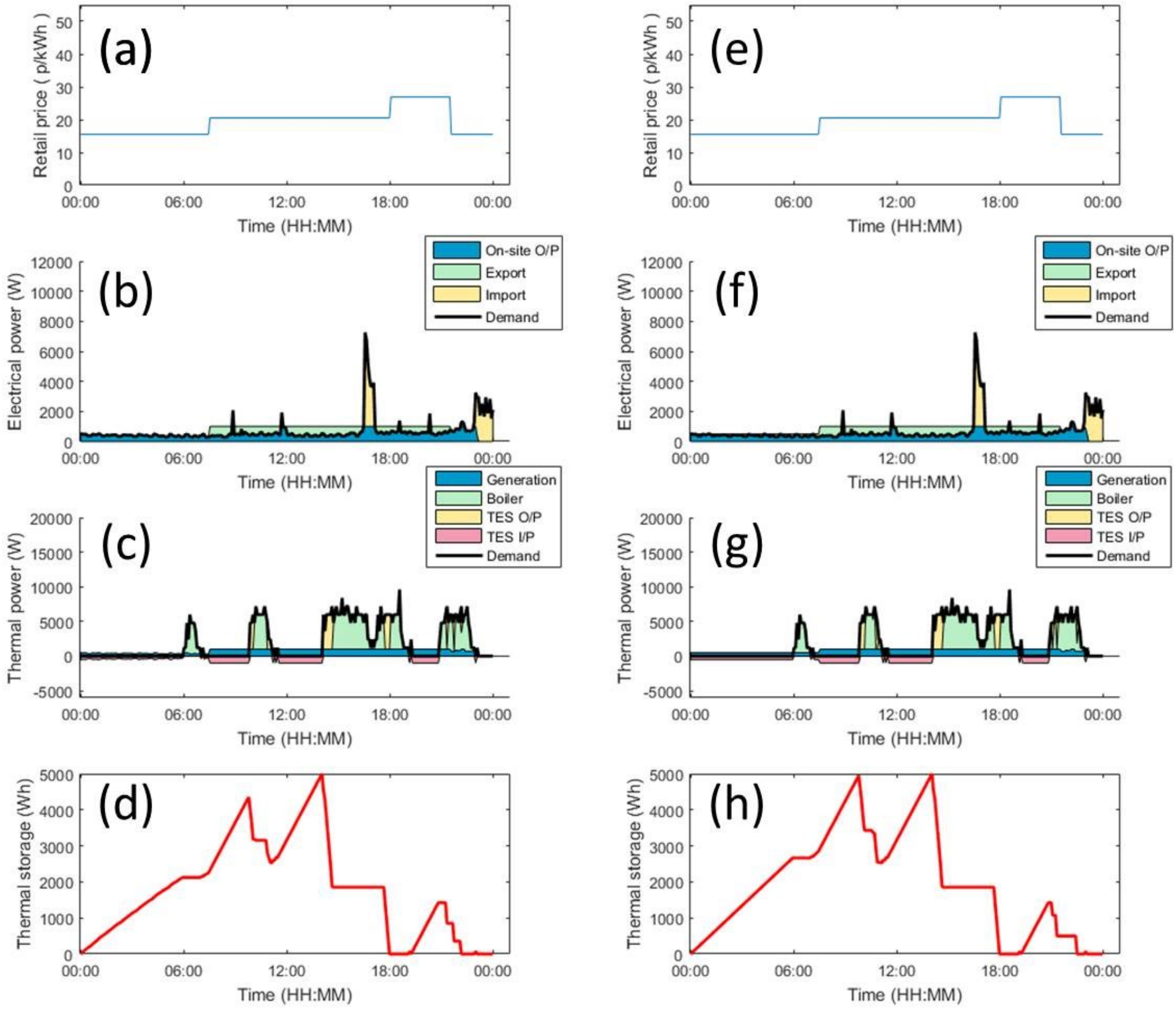

Figure 31 - Physical phenomena that drive performance. Best case: (a) to (d). Worst case: (e) to (h)

Even though the operating patterns look similar to the naked eye, the numbers in Table 12 show that there are subtle differences. It can be seen from Table 12 that some of the values of EAC are above the boiler baseline of £ 2630. The inclusion of start-up cost impairs performance even further in these cases. Hence there is room for accommodating start-up cost only when the EAC values are below the boiler baseline. The following section quantifies the maximum start-up cost that can be incurred before the system is no longer economically viable.

With this information, the maximum start-up cost can be calculated. This is shown in Table 17 and Table 18 . These tables contain omit entries where the EAC without start-up was greater than the boiler baseline. As expected, cases involving low turn down ratios and high ramping limits fare better than others. They produce the highest maximum allowable start-up costs. In Table 17, values below 1 kWh, which is the nominal value, are not economically viable. Hence the turn down ratio has to be lower than 0.35 if the system is to be economically viable with cold start-up. In contrast, a higher fraction of values in the hot start-up approach are above the nominal value of 0.2 kW in Table 18 and are hence economically viable. The system does particularly well when subject to low turn down ratios.

Table 17 - Maximum cold start-up cost (kWh)

		Turn Down Ratio				
	Value	0.2	0.275	035	0.425	0.5
Ramping Limit (W/5min)	100	-	-	-	-	-
	325	1.08	1.06	-	-	-
	550	1.13	1.11	0.97	0.49	-
	775	1.13	1.12	0.97	0.49	-
	1000	1.13	1.12	0.97	0.49	-

Table 18 - Maximum hot stand by power (kW)

		Turn Down Ratio				
	Value	0.2	0.275	035	0.425	0.5
Ramping Limit (W/5min)	100	-	-	-	-	-
	325	0.81	0.80	-	-	-
	550	0.85	0.84	0.73	0.31	-
	775	0.85	0.84	0.73	0.32	-
	1000	0.85	0.84	0.73	0.32	-

5.5. Conclusion

In this chapter, a novel approach to modelling fuel cell based micro co-generation in low carbon futures has been presented. It evaluates the impact of dynamic constraints on the economics of the fuel cell micro co-generation. Particular emphasis is laid on the difference between two control strategies: heat led and optimisation based and two start-up methods: allowing the unit to cool down (cold start-up) when inactive and keeping it on hot standby mode (hot start-up).

The results indicate that fuel cell based micro co-generation continues to be a promising technology even when potentially limiting dynamic constraints are taken into account. Economic viability is bent upon the use of an optimisation based control strategy. Heat led strategies are seen to push the equivalent annual cost above the boiler baseline even without accounting for start-up cost.

Even with an optimised operating strategy in place, the micro co-generation unit is rendered useless when subjected to a combination of low ramping limits less than 70 W/min and high turn down ratios above 35 per cent. The optimisation problem chooses to not use the fuel cell at all since the costs outweigh the benefits of onsite generation. Such combinations need to be avoided.

Given that the micro co-generation unit is operational, the start-up cost influences the economics more than the turn down ratio and ramping limits. Results indicate that the hot start-up approach offers much greater leeway to designers. The maximum allowable hot standby power is above the nominal value for turn down ratios less than or equal t0 0.425. The ratio between the maximum allowable and nominal hot standby power ranges from 1.5 to 4.2. The same cannot be said about cold start up. This approach requires turn down ratios less than or equal to 0.275 to be viable. Here the ratio between maximum and nominal start-up cost ranges from 0.5 to 1.1. This is because the fraction of time spent in hot standby mode is less than ten per cent. Thus the unit is economically viable even if the hot standby power is considerably higher than the nominal value found in literature.

Future research can relay the control instructions from the optimisation problem to a transient model that incorporates component level detail. This analysis can reveal if the interactions between sub-systems and control loops cause the plant to be inefficient or stray outside the safe operating envelope. Improvements involving other objectives such as environmental performance and multi-criteria analysis are also potential future directions.

6. Absorbing Surplus Renewables via Residential Heating

6.1. Introduction

As governments take action to achieve climate change mitigation (United Nations, 2015), the energy mix is likely to include substantially larger proportions of solar and wind energy. High penetration of these sources leads to an energy system that is significantly different from the one seen today. Generation is tied to the vagaries of weather conditions: the factors that determine the magnitude of output, sunshine and wind speed are outside human control. At low penetration levels conventional dispatch-able units can be used to maintain quality and reliability of power supply. But the same cannot be said about potential futures where penetrations are much more significant.

Traditionally when generation exceeds demand, some power plants are asked to lower output in order to maintain system stability. This is achieved through the balancing mechanism. Fossil fuel generators pay to turn down output since they can save fuel. But renewable sources participating in the balancing mechanism have no such incentive since there is no fuel cost. On the contrary, turning down output is detrimental to the renewable source's business case as it loses out on subsidies it would have received if it were injecting that electricity into the grid. Today, such a situation is encountered when the electricity generated by the wind farms in Scotland cannot all be transmitted to England. If these power plants are asked to reduce their output, they charge the system operator a fee that is far in excess of the subsidies that they forgo (Renewable Energy Foundation, 2011). As the frequency of instances in involving surplus electricity is likely to increase with increasing penetration of renewable sources (H. Lund & Münster, 2003), the system operator needs a solution that can help avoid expensive constraint payments.

One potential way to tackle this problem of surplus electricity is to make use of the demand side of the electricity grid. The net load on the system could be modified such that it supports the needs of the supply side. This is known as Demand Side Management (DSM). As we move away from an energy mix dominated by fossil fuel to one dominated by solar and wind we are also transitioning from a demand-led electricity grid to a supply-led one. DSM is likely to play a prominent role in such a future since in addition to economic savings it also provides system operators with a plethora of benefits: an additional source of flexibility to handle contingencies, congestion management, deferring network reinforcement and avoiding investment in peaking plants (Siano, 2014).

The main novelty of this work is that it combines three factors:

1. The context of power system decarbonisation.
2. Use of a decentralised electricity price signal which is set to zero to incentivise consumption when surplus renewables are encountered.
3. Comparison of performance of electrical heating and cogeneration for an individual household using optimised control.

As discussed in detail in Section 2.3.4.3, the intersection of these three factors is virtually untreated by previous literature.

6.2. Background

6.2.1. Price Based Demand Response

Historically demand side management was done through load curtailment. The system operator would either remotely shut down certain loads or offer discounts/payments to loads to shut themselves down (Albadi & El-Saadany, 2008). But such a centralised approach is not suitable for large scale deployment of DSM. The computational effort of managing millions of appliances and privacy concerns over a single entity having access to all of the consumption data are major obstacles that stand in the way of a centralised system.

Consumers can be incentivised to modify their usage patterns without requiring access to information about each and every individual connected to the grid. This does not happen today since consumers pay a constant retail price for the electricity they use. Hence, the onus is on the utility to absorb the uncertainties related to net load variations. Since the consumers are not exposed to such variations they see no benefit in changing behavioural patterns to shift usage to periods that would reduce the stress and cost of supplying electricity. Implementation of a time varying electricity price can provide signals to the consumers to modify their load patterns.

Time varying electricity price signals have previously been implemented through the use of time-of-use tariffs. Such schemes have been showed to influence consumer behaviour to shift demand away from peak periods (Caves, Christensen, & Herriges, 1984; Torriti, 2012). Time-of-use tariffs vary over different times during the day, but the patterns themselves are not subject to regular change across days. Hence, such schemes are only meant to serve the long term objective of reducing demand during periods which are historically associated with system peaks. But such repeating patterns are not enough to handle surplus renewables. The occurrences of such events are highly uncertain, irregular and difficult to predict. Another price based scheme which is an improvement over time-of-use tariffs is Critical Peak Pricing (CPP). Here consumers receive reduced rated at non-CPP times, but are charged a premium rate for current drawn during a CPP event (Jazayeri et al., 2005). This scheme is also aimed at reducing system peaks or managing contingencies and cannot be used in its current form to handle surplus renewables.

The solution to this problem has to inherit the dynamic nature of CPP but has to induce an increase in demand instead of a decrease. This can be done by decreasing the electricity price in response to surplus renewables. But this does not mean we have to sacrifice the benefits related to peak pricing. The advantages of both approaches can be combined through the use of a real time pricing system that decreases prices when there is excess renewable electricity and increases prices during system peaks.

6.2.2. Controllable Devices in Residential Heating Systems

The dynamic nature of real time pricing exposes the consumer to the real cost of producing electricity. This could be viewed as a source of pain for the customer since the energy consumed by the house needs to be monitored continuously in order to be economical. On the contrary, with the help of controllable loads, demand side management can be achieved automatically without human intervention. Residential heating provides such controllable loads which can potentially serve as powerful resources that provide value to both the customer and the system operator. The main objectives of such a system is to provide the customer with energy and cost savings without degrading the comfort level experienced by the occupants.

At the heart of such a solution lies a thermal energy storage unit. Storage is crucial since it provides the system with the ability to shift demand in time. Heat supply technologies act as a sink for electricity which store heat to be used at a later point. Electrical appliances such as a resistive heater or heat pump can supply heat. Another technology that could provide value is a combined heat and power unit. These devices can act as a source of electricity so that the customer can gain from peaks in electricity prices and the network can gain from distributed generation instead of dispatching a peaking plant.

6.3. Methodology

6.3.1. Model Overview

The model used in this chapter is the same as the one used in Chapter 4. Hence the problem statement remains the same. This chapter also makes use of an energy mix that is characterized by high penetration of low carbon sources coupled with an electricity price regime that makes use of the Long Run Marginal Cost of electricity. The only difference here is that the retail price of electricity is set to zero when there is excess renewable generation. This is referred to as Demand Turn Up in the later sections. The system is said to have excess renewable generation when such sources have to be curtailed to maintain system stability. The rationale behind the Demand Turn Up concept is that residential heating systems can react to this change by increasing consumption. This chapter serves as an extension of Chapter 4 which allows residential heating systems to support the grid with regards to balancing of excess renewables.

This thesis aims to identify a decentralised mechanism to coordinate flexible resources that provides value to both the grid and the consumer. There is no previous basis related to tackling this challenge of excess renewables. A centralised system has been avoided since the onus is then on the system operator to manage millions of resources. Even if the system operator chooses to take on this responsibility, there are major obstacles in the form an overwhelmingly large mathematical problem that needs to be solved and sensitive privacy concerns that need to be managed.

A price signal provides a convenient way to manage these resources. It can be argued that negative prices or a lower positive price can also be used to the same effect. While such price signals will definitely affect the economics of the end consumer they are not expected to result in an operating strategy that is different from one that makes use of zero electricity prices.

The price is set to zero to mimic conditions that would be encountered in an electricity price regime based on the status quo, namely, the Short Run Marginal Cost of generation. In the short run electricity price regime, excess renewable generation would result in zero or negative electricity prices since such sources do not have an associated fuel cost.

Detailed descriptions of the power dispatch model and electricity price regimes have been covered in the previous chapters. The following sections will focus on the consumer side model which highlights the contributions of this chapter.

6.3.2. Individual Heating System Description

This model compares the operation of four different technologies within an individual household: a resistive water heater, a heat pump, a fuel cell micro cogeneration unit and a Stirling engine micro cogeneration unit. The baseline case makes use of natural gas boiler for heat and a connection to the central grid for electricity. The natural gas boiler is an auxiliary heat source for all the cases except the heat pump. The connection to the central grid is a supplementary source of electricity for all cases. All new technologies are also equipped with a thermal energy storage tank. The system is exposed to time varying electricity prices, import is charged at retail price and export attracts revenue at wholesale price. The inputs from the power dispatch model provide the wholesale price. Wholesale prices are uplifted by taxes, fuel duties and policy cost recovery based on data from the UK government (BEIS, 2016b) to calculate retail prices. As explained earlier, the house is offered free electricity from the central grid when there is excess renewable generation.

6.3.3. Mathematical Model

The model makes use of a mixed integer linear program. It is applied to a set of representative days in a year. Each day is divided into five minute intervals. The results from each day are weighted approximately equally to calculate the annual performance indices used for comparison. The structure of the optimisation problem can be summarised as:

- Objective
  - Minimize operating cost (for CHP this includes revenue from electricity export)
- Subject to
  - Electrical and thermal load balance
  - Feasible operating envelope
  - Thermal energy storage operation

Details regarding mathematical modelling of these constraints are presented in Section 0. Data sources and individual values are presented in Section 4.2.4 and in Appendix A.

6.4. Results and Discussion

6.4.1. Comparison of Operation

In this section we first compare the operation of the optimised residential heating system technologies with and without Demand Turn Up (DTU). As explained earlier, a Demand Turn Up event refers to the use of zero prices when there is an excess of renewable generation. The modified retail price of electricity is shown in the top row of each figure. The rest of the subplots describe electrical power balance, thermal power balance and operation of thermal storage. This discussion is followed by a comparison of overall performance that supports the conclusions.

6.4.1.1. Resistive Heater

Operation with the original retail price of electricity is shown on the left side of Figure 32. This price which is based on the Long Run Marginal Cost of electricity remains above 15 p/kWh throughout the day as seen in Figure 32(a). Such high electricity prices do not provide scope for using the resistive heater as seen in Figure 32(b). Consequently, the thermal energy storage unit does not charge or discharge as seen in Figure 32(c) and Figure 32(d). All thermal demand is met using the natural gas boiler.

The electricity price drops to zero at various points during the day if Demand Turn Up is active as seen in Figure 32(e). As a result, the resistive heater is switched on when free electricity is available as seen in Figure 32(f). The red curves in the negative direction in Figure 32(g) represent charging of the thermal energy storage unit. This can also be seen through the corresponding increases in state of charge of the thermal storage unit in Figure 32(h). Since free electricity is available at many points during the day, the system is able to charge the thermal storage unit to full capacity, discharge, and repeat this process more than once as seen in Figure 32(h).

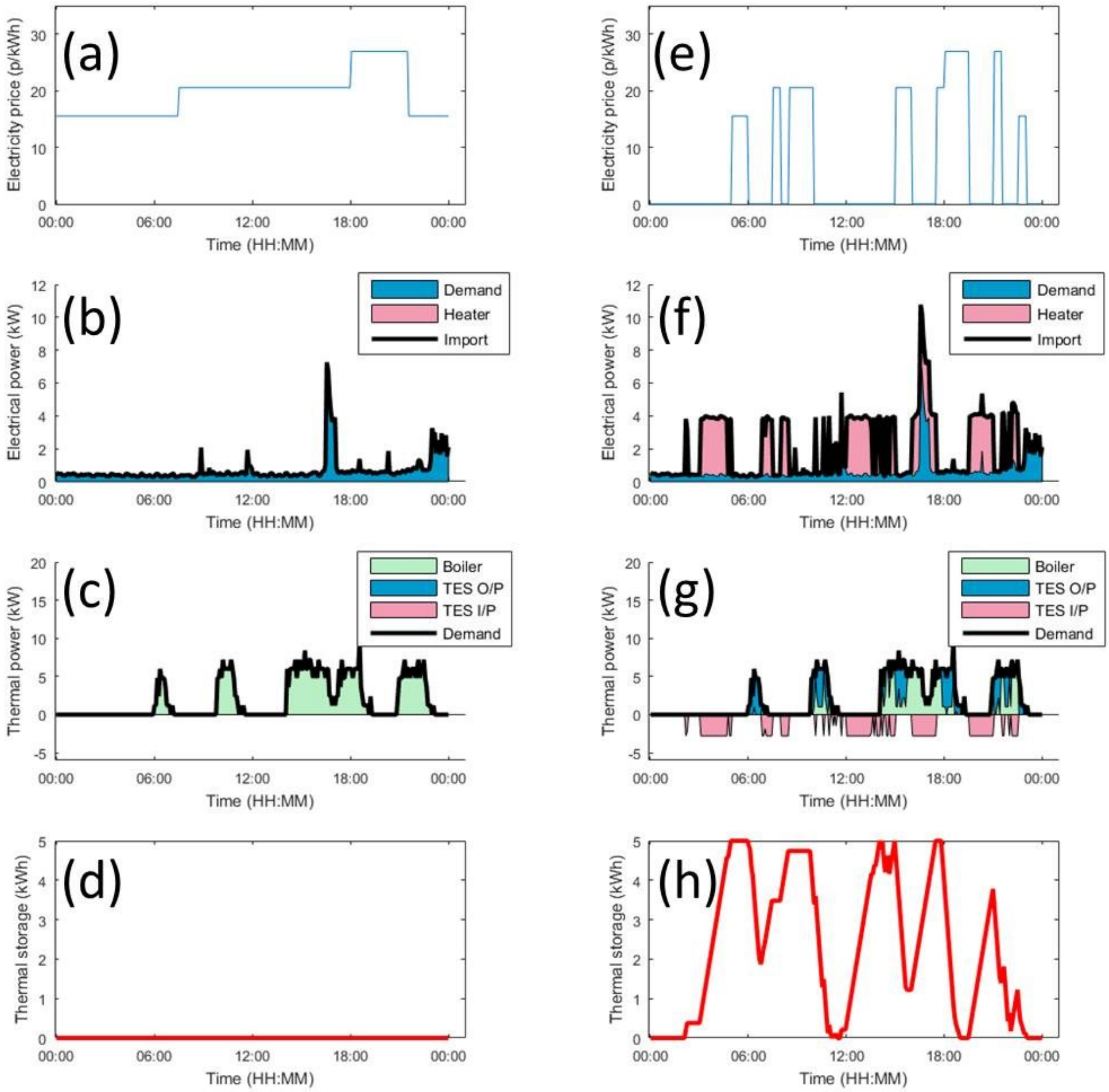

Figure 32 - Operation of the Resistive Heater: Without DTU ((a) to (d)) and With DTU ((e) to (h))

6.4.1.2. Heat Pump

The heat pump is different from the other technologies in the sense that it uses electricity to supply heat instead of natural gas. As a result of this, the shape of the electricity imported is influenced by the heat demand. The change in shape is clearer without DTU as seen in Figure 33(b). In contrast to the resistive heater, the thermal storage unit is not completely dormant in this case. It stores up energy at the beginning of the day to supply heat demand when the electricity prices are above 25 p/kWh around 9 PM as seen in Figure 33(c) and Figure 33(d).

Reliance on electricity allows the heat pump to take advantage of the free electricity available with DTU. The red patches in Figure 33(g) show the heat pump charging the thermal storage unit during such times. The blue patches in Figure 33(g) show the heat pump discharging the thermal store when system has to pay for importing electricity. The shape of electricity imported does not follow heat demand with DTU since the use of the thermal storage unit shifts demand to periods with free electricity. As with the resistive heater, the system charges the thermal store to full capacity and discharges it more than once.

6.4.1.3. Fuel Cell Based Micro Cogeneration

High electricity prices and low natural gas prices are encountered when the system is operated without DTU. These conditions are conducive for the operation of fuel cell based micro cogeneration units as seen in Figure 34(b). The coincidence of electricity and heat demand also favours the use of cogeneration as seen in Figure 34(b) and Figure 34(c). The efficiency gains from combined generation of heat and electricity are particularly clear when coincidence levels are high. The thermal storage unit allows the cogeneration unit to remain active continuously while storing up heat as shown in Figure 34(d). This can be seen in the charging of the thermal store until 2 PM.

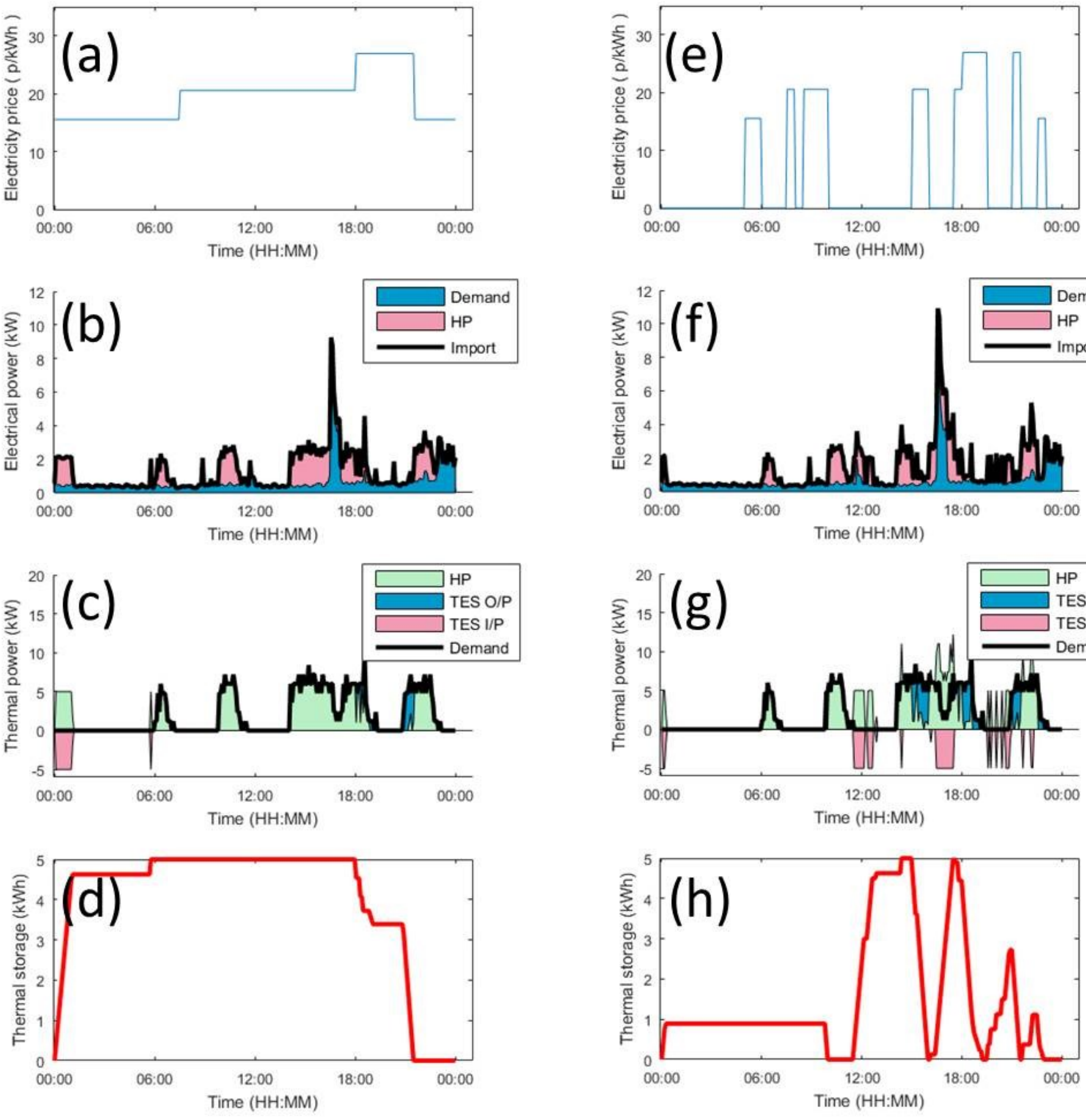

Figure 33 - Operation of the Heat Pump: Without DTU ((a) to (d)) and With DTU ((e) to (h))

The situation changes when DTU is enabled. The system no longer encounters high electricity prices throughout the day. Utilisation of the cogeneration unit is much lower as seen in Figure 34(f) and Figure 34(g) since it is more economical to use grid electricity and the natural gas boiler. The cogeneration unit is activated only when the electricity prices are high as seen by the sporadic appearance of blue patches in Figure 34(f). This does not offer much scope for the thermal storage unit to be used as seen in Figure 34(h).

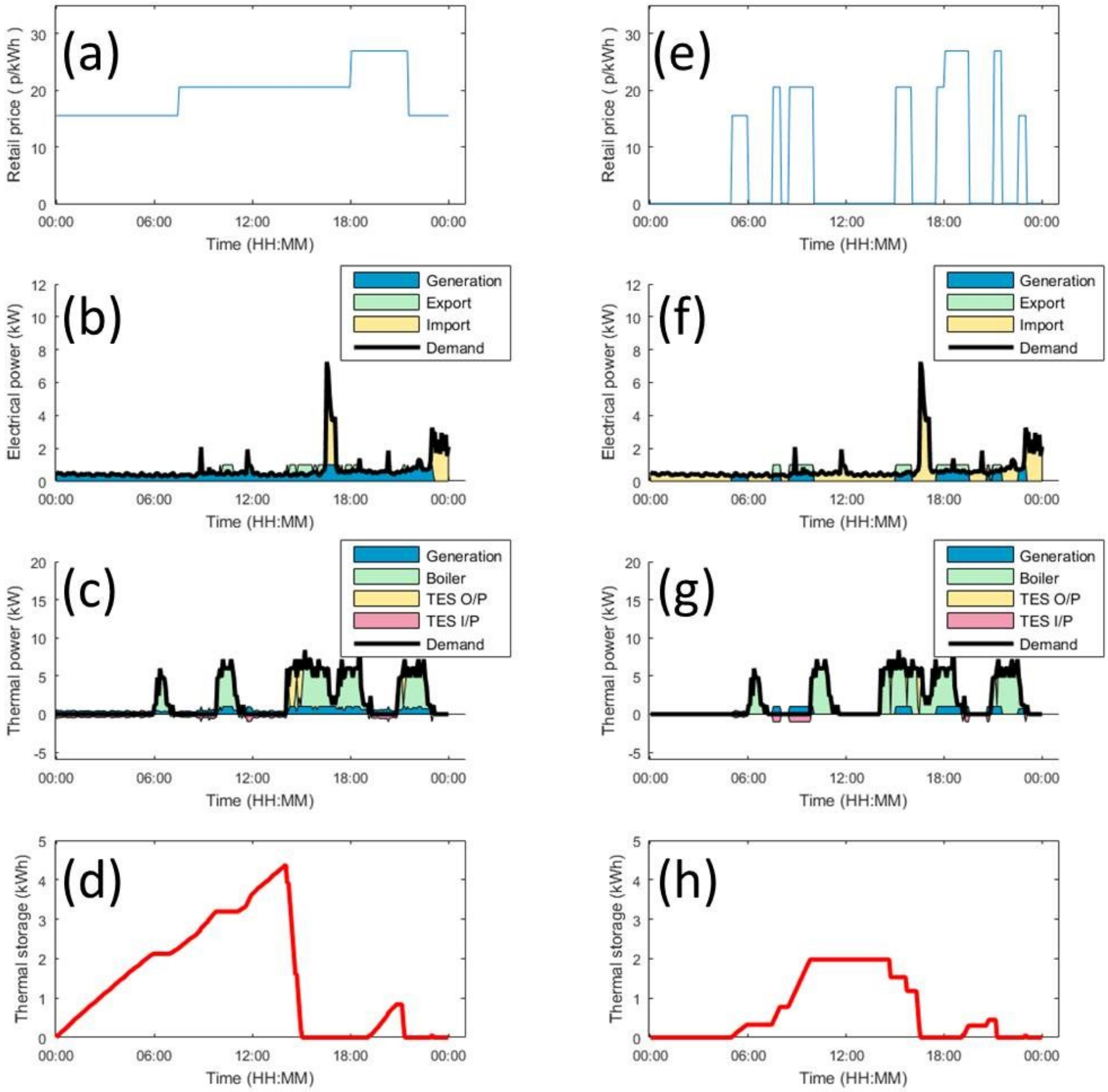

Figure 34 - Operation of the Fuel Cell: Without DTU ((a) to (d)) and With DTU ((e) to (h))

6.4.1.4. Stirling Engine Based Micro Cogeneration

The Stirling engine is different from the fuel cell in terms of heat to power ratio. It produces much more heat per unit of fuel consumed in comparison to the fuel cell. This means that unless a high heat load occurs at the same time as an electricity load, efficiency gains are not significant. This can be offset to a certain extent because of the presence of a thermal store as seen by the red patches in Figure 35(c). But utilisation of the Stirling engine cannot match that of fuel cell even with the inclusion of a thermal store as seen in Figure 35(b). Another disadvantage of the high heat to power ratio is that it prevents the Stirling engine from exporting electricity to the grid.

Utilisation levels go down even further when DTU is enabled. But the cogeneration unit continues to operate when the electricity prices are high as seen in Figure 35(f). This happens even when there is no heat demand as seen around 9 AM in Figure 35(g). Free electricity prompts more use of the natural gas boiler as seen in Figure 35(g) in contrast to its counterpart in Figure 35(c). The use of the thermal store also decreases when DTU is enabled as seen in Figure 35(h).

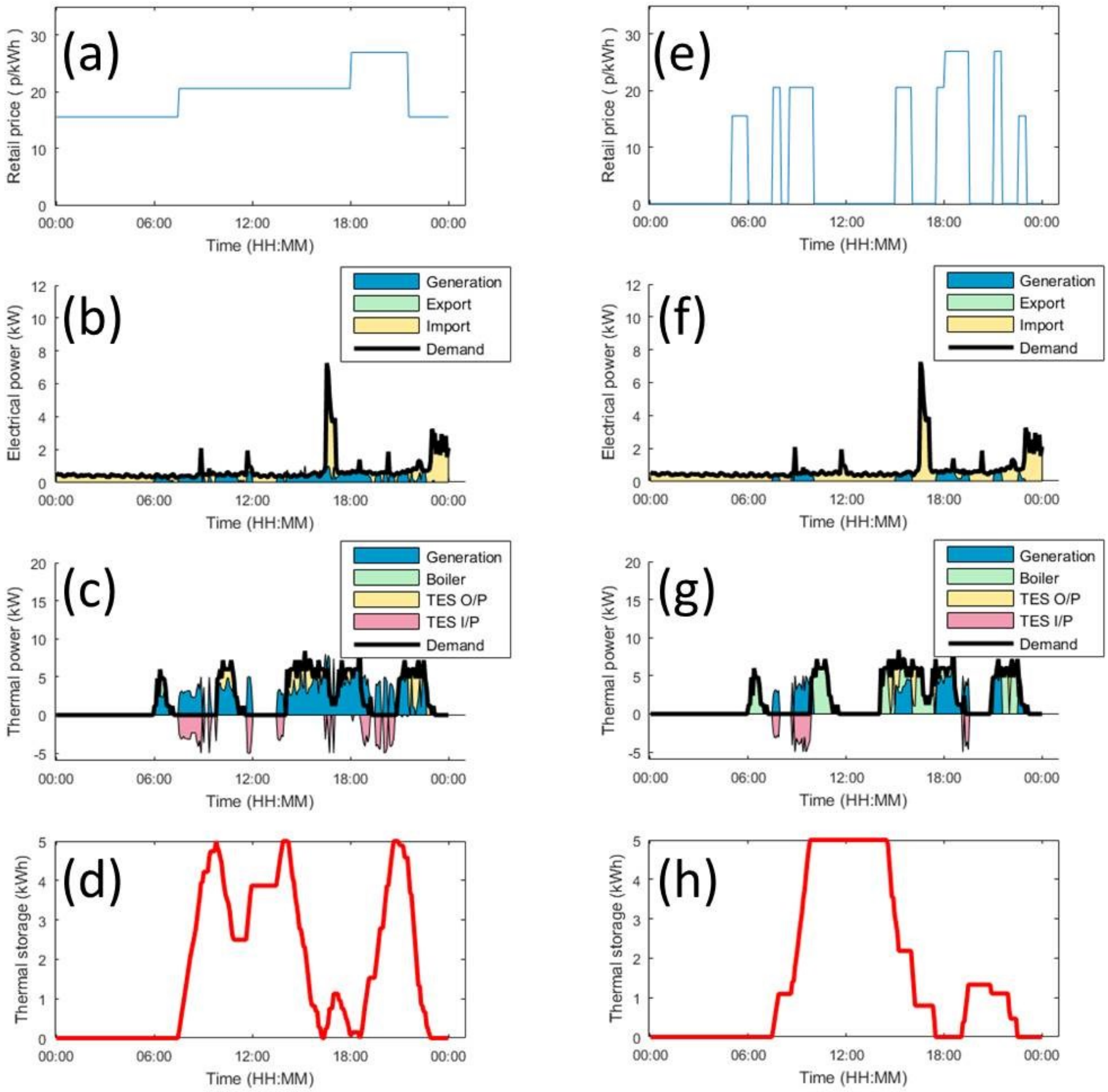

Figure 35 - Operation of the Stirling Engine: Without DTU ((a) to (d)) and With DTU ((e) to (h))

6.4.2. Comparison of Overall Performance

Equivalent Annual Cost (EAC) is the index used to measure economic performance in this study. It includes annualised capital, operational expenses, and export revenue. A formal definition has been provided in Chapter 4. Figure 36 presents a comparison of economics with and without Demand Turn Up (DTU).

All technologies are comparable in terms of economic competitiveness when considering the case without Demand Turn Up. High electricity prices lead to high operating costs for the heat pump. It can be seen that the boiler baseline and the resistive heater have similar EACs. This implies that the resistive heater was not offered much scope to charge the thermal store. Thus the resistive heater was not able to reduce the amount of natural gas used. High electricity prices provide conditions that are favourable for the use of fuel cell based cogeneration. There is a considerable decrease in the amount of electricity imported when the fuel cell is in use. Savings from onsite generation of electricity coupled with the revenue from export drive the EAC below the boiler baseline making the fuel cell the only technology that is economically viable. Although high electricity prices favour cogeneration, the Stirling engine does not fare well because of its high heat to power ratio. It is not able to generate enough electricity to reduce import from the grid, resulting in an equivalent annual cost higher than the boiler baseline.

Equivalent Annual Costs of all technologies are lower with Demand Turn Up as seen in Figure 36. This can be attributed to the reduction in the cost of electricity from the central grid. The introduction of Demand Turn Up tilts the balance in favour of technologies that use electricity. The resistive heater and heat pump are able to take advantage of periods with free electricity. Equivalent Annual Costs of both technologies are significantly lower than the boiler baseline. The fuel cell is no longer economically viable. Even though the EAC of the fuel cell has reduced in comparison to the case without Demand Turn Up, the boiler baseline has shifted downwards as well. Savings and revenue from export are not enough to justify investment in the fuel cell. Low electricity prices mean that the Stirling engine's high heat to power ratio does not limit performance as much. The Stirling engine is able to offset the natural gas boiler enough to result in an EAC lower than the fuel cell.

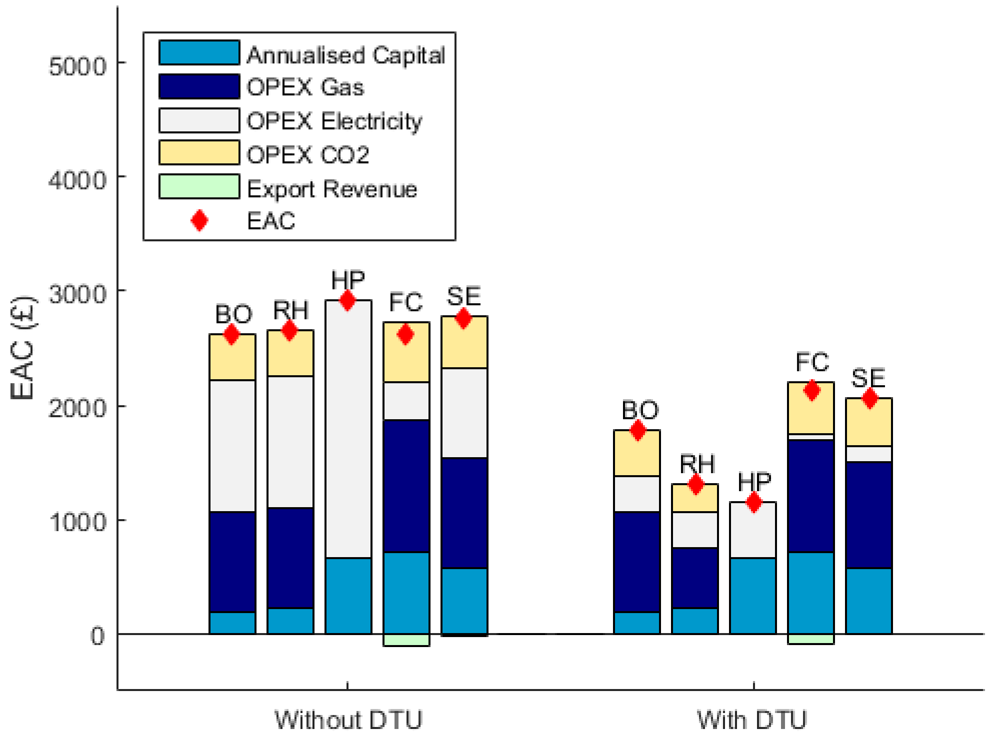

Figure 36 - Comparison of Equivalent Annual Cost. (DTU – Demand Turn Up, BO—Boiler, RH—Resistive heater, HP—Heat pump, FC—Fuel cell micro cogeneration, SE—Stirling engine micro cogeneration).

A comparison of environmental performance is shown in Figure 37. The heat pump is the clear leader with and without Demand Turn Up. The reason for this is the low carbon intensity of electricity in the low carbon future. The resistive heater is identical to the boiler baseline without Demand Turn Up. This implies that the resistive heater was not used at all in the case without Demand Turn Up. The resistive heater is able to produce emissions lower than the boiler baseline when Demand Turn Up is enabled. Although emissions from electricity import have increased, reduced reliance on the natural gas boiler has lowered the overall emissions from the resistive heater. Emissions from both fuel cell and Stirling engine cogeneration units are above the boiler baseline with and without Demand Turn Up. Accounting for onsite generation lowers the net emission values slightly but not enough to drive them below the boiler baseline.

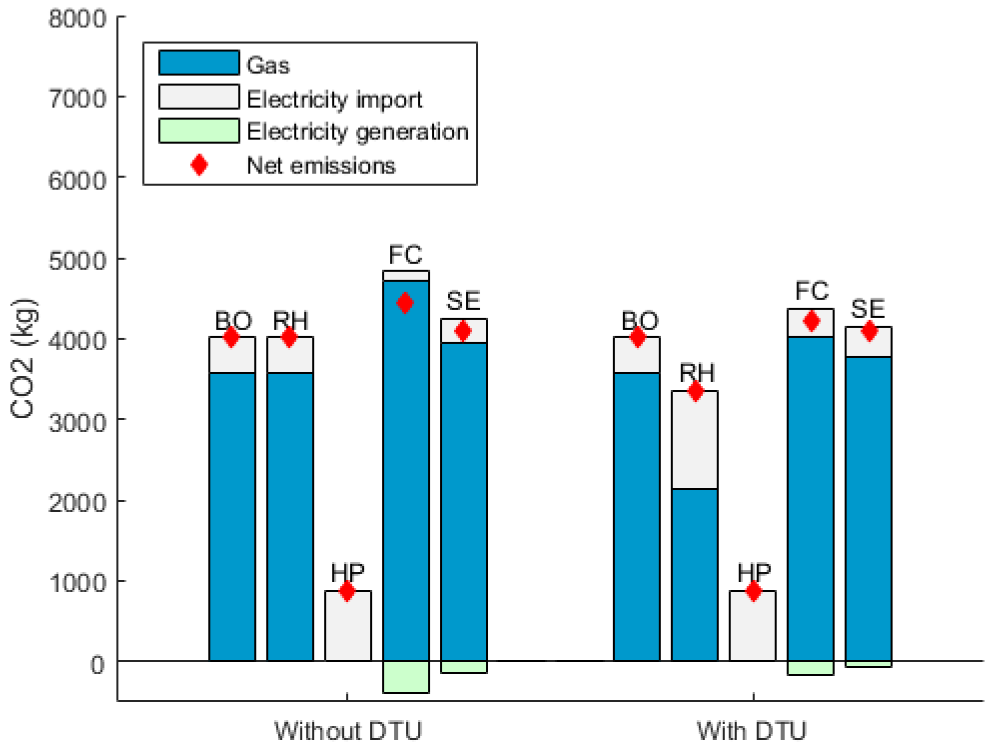

Figure 37 - Comparison of Emissions. (DTU – Demand Turn Up, BO—Boiler, RH—Resistive heater, HP—Heat pump, FC—Fuel cell micro cogeneration, SE—Stirling engine micro cogeneration).

6.5. Conclusion

In this chapter, we evaluate the potential for using residential heating systems as a means to absorb surplus renewables in low carbon futures. The system aims to implement Demand Turn Up by offering free electricity during periods of excess renewable generation. Particular emphasis is laid on the operating strategies, economic and environmental performance of the different heating technologies considered.

Technologies which make use of electricity thrive when Demand Turn Up is enabled. Demand Turn Up allows the resistive heater and the heat pump to capitalise on the occurrence of zero electricity prices. These technologies are able to charge the thermal store using free electricity and discharge the thermal store when electricity prices are high. The savings from such actions are enough to reduce the equivalent annual cost by 50 per cent for the resistive heater and by 60 per cent for the heat pump.

Cogeneration units on the other hand do not perform well when Demand Turn Up is enabled. The lowering of electricity prices to zero diminishes the value gained out of combined generation of heat and power. These technologies are to be avoided in systems with Demand Turn Up since they are not meant to increase consumption and they are not economically viable.

Technology adoption will not only be based on performance but also ease of installation and upfront cost of the technology. Heat pumps are disadvantaged by high upfront costs and inconveniences associated with installation. Issues related to upfront costs can be alleviated by policy support but the pains related to installation still remain. Resistive heaters are relatively easy to install and involve low upfront costs. Hence resistive heaters are likely to be the technology of choice for implementing Demand Turn Up, though this could lead to significantly higher primary energy consumption with related environmental impacts.

Future research can consider the integration of models describing the supply and demand sides. This is important since there is a possibility of rebound peaks appearing due to a large number of devices reacting to a single price signal. Staggered price change according to location and density of flexible devices can help avoid such peaks. Another factor that requires attention is the uncertainty associated with forecasts of excess renewable generation. Stochastic programming can be used to address the risks related to intermittent resources.

7. Conclusions and Future Work

7.1. Summary and Contributions

Decarbonisation of electricity and heat sectors are important challenges that need to be tackled if the UK is to adhere to its carbon targets. Unlike the transport sector, where decarbonisation is reliant on technology innovations, the technologies needed in the electricity and heat sectors have existed for decades. The magnitude of the challenge should not be underestimated and could potentially involve several million heating installations and several thousand megawatts of generation by the year 2050. Furthermore, in addition to changes in technology mix, the ability of the individual consumer in the heat sector to react in real time to changes in the supply side of the electricity sector is likely to take centre stage as we move from a centralised to a more decentralised paradigm in the coming decades. Since these factors are not fully understood by existing literature, there is a pressing need for computational tools that can assess the changes that will be spurred on by this transformation.

The main contribution of this thesis can be summed up as follows:

> **Development of a modelling framework to study the impact that a transformation of the energy mix in the power sector has on a traditionally carbon intensive domestic heat sector.**

To this end, this thesis has introduced and examined the operation of both the electricity grid and optimised residential heating systems in a low carbon future.

In Chapter 3 we discuss the use of a power dispatch model that simulates generator operation in a scenario which involves high penetration levels of solar, wind and nuclear sources. This presents an optimisation model that has enough technical detail to represent the evolution of the commodity price of electricity when there is a fundamental change in the system twenty years into the future.

This level of technical detail is necessary since there is no basis to assume that patterns seen in historical data will remain the same when considering long term prediction horizons and radical changes in the system. Another important feature of this model is that it improves upon the existing methods that determine the commodity price of electricity. Start-up costs are a significant portion of the cost of generation of electricity. Failing to account for them could grossly underestimate the commodity price of electricity and present a distorted picture of generator operation in the future. Current methods based on the dual value of the energy balance constraint are not capable of accounting for changes in integer variables and hence do not account for start-up costs. This model solves this problem by making use of the dispatch decisions ex-ante to incorporate start-up costs into the commodity price of electricity.

Decarbonisation of the power sector is expected to be fundamental to climate change mitigation in the future. Hence any assessment of other sectors must be performed under the context of power system decarbonisation. This is crucial because changes in the power sector have far reaching implications on other sectors such as buildings and heat. In Chapter 4 we examine how performance of different residential heating technologies is affected by a transformation of the energy mix in the electricity grid.

Another important issue is that the introduction of low carbon generation technologies which have negligible fuel costs can possibly cripple the business case of dispatch-able units due to a decrease in the commodity price of electricity. Hence we introduce an alternative electricity price regime which allows dispatch-able units to recover their capital cost and protect themselves from reporting a loss. Although this may address the issues of dispatch-able generators in the power sector, it is likely to affect the performance and hence technology adoption in the residential heating sector. Chapter 4 decisively quantifies the impact of a change in electricity price regime on the operation, economic viability and emissions of various heating technologies such as resistive heaters, heat pumps, fuel cell based micro cogeneration and Stirling engine based micro cogeneration.

In Chapter 5 fuel cells are studied since they are an emerging technology with distinct advantages such as a reduction in primary energy consumption and transmission losses. But fuel cells consist of a huge range of subsystems which have to be coordinated in order to function. This introduces possibly limiting dynamic characteristics which could affect performance. This model provides a simple approach that makes use of mathematical abstractions to represent dynamic characteristics in a mixed integer linear program. It quantifies the impact of different dynamic characteristics on performance of fuel cell based micro cogeneration. An important implication of this information is that this model can now identify which characteristics are likely to significantly affect performance. Hence it provides an effective way to feed information back to the design process of future fuel cell based systems.

The transformation of energy mix also introduces problems related to the balance of supply and demand. Low carbon futures are likely to be riddled with instances in which the generation from intermittent and inflexible sources is far in excess of the load served by the system. Curtailment is likely to involve high constraint payments to renewable sources and failing to curtail threatens the stability of the system. Chapter 6 presents a solution that makes use of residential heating systems to absorb this excess generation. Residential heating systems are an attractive way of solving this problem without excessive investment in new infrastructure. But centralised coordination is a challenging task due to prohibitive computational costs and sensitive privacy concerns. Chapter 6 makes use of a decentralised electricity price signal that utilises tractable optimisation problems and does not require consumers to reveal information about their usage patterns to a central authority. Consumers are incentivised to increase demand by offering them free electricity during times of excess renewable generation. This is an effective way to provide value to both the consumers and the electricity grid without compromising the comfort of consumers and reliability of the overall system.

7.2. Key Overall Conclusions

The main premise in this thesis is that the results from the power dispatch model will affect the results from the residential heating system model. The results from the individual chapters evaluate the extent to which this premise holds under various conditions.

In other words, this thesis analyses the extent to which radical changes in the power sector influence the performance of technologies in the domestic heat sector. It is clear that transitioning to a low carbon future cannot be done without changes to the electricity markets currently in place. Changes to the electricity market are seen to affect operation and hence technology choices in the domestic heat sector. Therefore the interplay between the electricity and heat sector is likely to assume significance in low carbon future. Thus this thesis serves as a good foundation for future research regarding the interactions between these two sectors.

Cogeneration technologies make more economic sense when the difference between electricity and natural gas prices is large. Such conditions are encountered when the electricity price is based on the

Long Run Marginal Cost of generation. Fuel cells have more potential in this regime since their low heat to power ratio allows them to offset a greater fraction of electricity imported from the grid in comparison to Stirling engines. For the same reason, fuel cells are not limited by the availability of heat demand in order to export electricity when high prices are encountered. Nevertheless, even fuel cells require a dwelling with large electrical and thermal demand in order to access economic value. Operational expenses related to electricity are reduced by 70 per cent in comparison to the baseline while those related to natural gas increase by 30 per cent for the fuel cell. Export revenue of around £150 per year also plays a role in making the fuel cell economically viable.

Environmental performance of cogeneration units in a low carbon future is very different from that in a present day scenario. The current carbon intensity of the central grid is between 300 g/kWh and 400 g/kWh. Hence onsite generation has a significant impact on emission savings in comparison to the baseline involving the central grid. In contrast the carbon intensity of the central grid is only 75 g/kWh in the low carbon scenario. This greatly erodes emission savings. In fact, emissions rise above baseline levels since economic optimisation strives to use more natural gas and export more electricity when the prices are high.

When the carbon intensity of the central grid is varied, emissions from the heat pump increase. Beyond 275 g/kWh, heat pump is no longer the lowest emitter of carbon dioxide in the medium sized house. Fuel cells are able to outperform heat pumps leading to 35 per cent lesser emissions in this case since they receive equivalent credits for onsite generation which drives down emissions. Performance of the Stirling engine on the other hand only improves marginally. It does not overtake heat pumps even when carbon intensity of the central grid is 400 g/kWh due to low onsite generation.

The resistive heater and heat pump are better suited for situations which involve low electricity prices. These technologies are ideal for absorbing low cost excess renewable generation. When combined with a thermal storage unit, these technologies can effectively decouple thermal generation and demand. The savings from such actions are enough to reduce the equivalent annual cost by 50 per cent for the resistive heater and by 60 per cent for the heat pump. Cogeneration units are forced to turn down output when electricity prices are low. Low utilisation leads to lower savings and hence deters investment in these technologies.

7.3. Conclusions Relevant to Modelling and Technology Development

Power system decarbonisation is characterised by making use of a power dispatch model based on unit commitment in this thesis. Before proceeding to the future scenario we must first assess whether the model provides a realistic representation of the commodity price of electricity. This is done through a validation process. Actual commodity price data from the electricity market in the year 2015 is compared to the output of the power dispatch model. Even though this involves short term prediction horizons which give econometric methods the edge, the error values of 14.1 per cent and 14.9 per cent for the competing approaches indicate that the accuracy of the proposed bottom up approach is comparable.

When the penetration of renewables is higher, the cycling patterns undergo significant change. Start-ups are more frequent and the units which are started up stay online for relatively short durations. This means that dispatch-able units are coming online briefly due to variations in renewable generation and the inability of nuclear generators to ramp output in order to compensate. Hence a pivotal role could be played by new sources of flexibility in low carbon energy systems.

Combining the results from the unit commitment model with the residential heating system model allows us to feed information back to the design process. This is particularly useful for fuel cells which are considered an emerging technology. The impacts of dynamic characteristics of fuel cells need to be evaluated since a plethora of subsystems need to be coordinated in order to function. Dynamic characteristics considered include start-up cost, ramping limit, turn down ratio, minimum up time and minimum down time. This analysis revealed that the operating strategy has a pronounced impact on the economics of fuel cell based micro cogeneration unit. A heat led strategy is not viable even when subjected to high ramping limits and low minimum up/down times. The Equivalent Annual Cost is above the boiler baseline of £2630 for the entire sensitivity range considered in this study. An optimisation based operating strategy results in lower Equivalent Annual Costs. It is seen that high turn down ratios above 35 per cent and low ramping limits below 80 W/min render the fuel cell useless. Utilisation levels are zero since onsite generation is deemed to be more expensive than the boiler- central grid combination. These are red flags that are important outputs of the model.

Another significant development is the difference between hot can and cold start-up. While an optimisation based control strategy seems to deploy identical operating profiles irrespective of the type of start-up the economic implications are not the same. The optimisation based operating strategy tends to keep the fuel cell operating for long periods of time in order to maximize savings. This means that the fuel cell is inactive only for a small fraction of the day. Therefore in hot start-up mode the fuel cell is kept on hot standby for less than ten per cent of the time. This gives hot start-up an advantage over cold start-up. The maximum allowable hot standby power is always above the nominal value and in some cases it is up to four times greater. The same cannot be said about the maximum allowable cold start-up cost which is sometimes lower than the nominal value.

The model reveals that minimum up time and minimum down time do not have a significant impact on the performance of fuel cell based micro cogeneration when optimisation based control is used. This is because the cogeneration unit is either kept active for a large portion of the day or it is not used at all as discussed earlier. Since the cogeneration unit does not start and stop often, minimum up time and minimum down time do not need to be prioritised during development.

Irrespective of the dynamic characteristics taken into account the heat to power ratio is a deciding factor for cogeneration units when electricity prices are high. This is clearly evident in the inability of Stirling engines to produce savings that are enough to justify investment. The fuel cell on the other hand is able produce up to 380 per cent more electricity to drive down the equivalent annual cost. If electrical efficiencies can be increased further fuel cells could become economically viable even when onsite demand is not large.

Technology adoption is likely to be dependent on factors such as perceived comfort and inconvenience of installation as well. Perceived comfort will not differ between technologies since the model is designed to supply all the heat demanded by the house at any point of time. Unlike other approaches that may make use of the house itself as a source of passive storage our approach does not tamper with the temperature setting which affects comfort. Heat pumps may be inconvenient to install. This could lead to consumers passing over heat pumps for resistive heaters when Demand Turn Up is enabled.

7.4. Conclusions Relevant to Policy Making

The power dispatch model shows that an energy mix dominated by low carbon sources results in considerably lower electricity prices. The average price is nearly halved. Commodity prices of electricity determine whether a generator is able to break even while selling electricity. This means that a transition to a low carbon energy mix puts dispatch-able units at risk of not being able to recover their capital investment. Since such units are critical for system reliability a different market structure that augments their revenue is necessary.

A new electricity price regime is proposed to address this concern. It incorporates capital costs and utilisation into the electricity price by making use of the Long Run Marginal Cost of generation. A fixed power purchase agreement based on long run costs are assigned to each generator type including renewable sources. Thus renewable sources are no longer associated with zero marginal costs. The use of Long Run Marginal Costs provides bolsters the revenue stream of dispatch-able units and does not allow electricity prices to drop to zero even when penetration of low carbon sources is high. It is clear that more research is necessary in this area before an alternative electricity market can be put in place. To this end, this thesis proposes a simple yet reasonable direction for modelling which provides lessons for policy.

The electricity price regime based on long run costs allows cogeneration units to offset expensive electricity from the central grid and become a more economically attractive investment. Although they result in lower equivalent annual costs for the consumer, they do not result in the lowest emissions. The low carbon intensity of the central grid works against cogeneration units. Prolific usage of natural gas to export electricity ends up raising emission levels above the boiler baseline. Heat pumps result in the lowest emissions irrespective of electricity price regime. This is true even when considering the use of demand turn up to absorb excess renewable generation. Thus large scale adoption of heat pumps is one potential measure that can reduce emissions and improve demand side flexibility in a low carbon scenario. But heat pumps also have issues in the form of high upfront costs and reinforcements of the transmission and distribution networks for the system operator. Policy support can help address concerns about upfront costs for the consumer. Hence the system operator will have to trade off emission reduction against investment in network infrastructure.

It is envisioned that the feed-in tariff for generation will not be in use in the year 2035. Hence some other form of performance based policy to reduce emissions will be necessary. The results indicate that the forecast of the Non Traded Price of Carbon found at the time of writing is not sufficient to drive emissions down. Hence stronger policy instruments are necessary in the medium term.

Overall, this work has demonstrated that an important dynamic exists between electricity sector decarbonisation, market arrangements that drive electricity prices and technology choices in residential heating systems. Policy makers should be mindful of this dynamic when designing markets and policy instruments of the future.

7.5. Future Work

This thesis has helped identify several important research areas that deserve attention in future works. The most natural extension of the models in this thesis is the integration of the supply and the demand side. High penetration of optimised residential heating systems would result in a large number to devices reacting to a change in price signal from the supply side. Thus the change in overall demand would prompt a change in operation of the supply side. This applies to all electricity price regimes described in this thesis and particularly to the case with demand turn up where zero prices are involved.

The integration of the supply and demand side is likely to involve iterative loops which exchange electricity price and overall change in demand. The use of a unit commitment problem which represents each individual generator with a binary variable in such loops will result in large computation times. Clustering similar generators into a single generator type can significantly reduce computation times and allow for simulation of a larger number of representative days.

Systems with large penetration of optimised devices will also activate transmission constraints in the electricity grid. Incorporation of spatial and temporal dimensions to demand will allow the supply side to better describe changes in operation. Hence transmission limits have to be imposed on the unit commitment problem. Modifications involving security constrained unit commitment and optimal power flow are also applicable to such cases.

Another area that stems from the models presented here is the impact of optimised heating systems on generation capacity. While high prices are likely to move demand away from peak periods requiring lesser generation capacity, large scale deployment of heat pumps could require an increase in generation capacity. The investment patterns that will emerge from the simultaneous changes in the supply and demand side are not fully understood yet.

The treatment of uncertainty in this thesis involves the use of sensitivity analyses where the change in performance is measured with respect to a change in input variable. These models would benefit from a more detailed characterisation of uncertainty through the use of a stochastic programming framework. Such a framework can assess the risk associated with predictions of renewable output, electricity price, fuel price and demand profiles used in this thesis.

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Appendix A – Parameter Ranges and Chosen Values

Table 19 - Heating system parameters in the year 2035[5]

Parameter	Description	Units	Range	Chosen Value	Ref.
α_{CO2}	Non-traded price of carbon	£/tonne	113	113	(BEIS, 2017c)
α_{gas}	Natural gas price	p/kWh	4.5	4.5	(BEIS, 2016b)
η_B	Efficiency of natural gas boiler	-	0.8-0.9	0.86	(De Paepe, D'Herdt, & Mertens, 2006; Kong, Wang, & Huang, 2005; Lazzarin & Noro, 2006; Qu, Abdelaziz, & Yin, 2014; Sun, Wang, & Sun, 2004)
η_{ch}, η_{disch}	Charging/discharging efficiency of TES	-	0.4-0.97	0.9	(Hahne & Chen, 1998; Lavan & Thompson, 1977; Verda & Colella, 2011)
η_{el} (Fuel cell)	Electrical efficiency	-	0.3-0.45	0.45	(International Energy Agency, 2010; Korsgaard, Nielsen, & Kær, 2008; Parsons Brinckerhoff, 2012)

[5] Note that a complete fuel cell micro-CHP system requires a fuel cell, fuel cell reformer, TES and boiler. Likewise a complete Stirling engine system requires a Stirling engine, TES and a boiler.

η_{th} (Fuel cell)	Thermal efficiency	-	0.39-0.48	0.45	(International Energy Agency, 2010; Korsgaard et al., 2008; Parsons Brinckerhoff, 2012)
η_{el} (Stirling engine)	Electrical efficiency	-	0.125-0.22	0.10	(Barbieri, Melino, & Morini, 2012; Bianchi et al., 2013; Orr, 2012)
η_{th} (Stirling engine)	Thermal efficiency	-	0.6-0.8	0.80	(Barbieri, Melino, et al., 2012; Bianchi et al., 2013; Orr, 2012)
Ψ (Boiler)	Upfront cost	£	2200-2500	2328.1	(Carbon Trust, 2011; Daly & Fais, 2014; Weiss et al., 2010)
Ψ (TES)	Upfront cost	£	50-1300	415.4	(Daly & Fais, 2014; IRENA, 2013; Mondol, Smyth, Zacharopoulos, & Hyde, 2009)
Ψ (Heat pump)	Upfront cost	£	6653-35363	7587.3	(Daly & Fais, 2014; Sweett Group for DECC, 2013)

Ψ (Fuel cell)	Upfront cost	£	1775-15152	5037	(Daly & Fais, 2014; Nelson, Nehrir, & Wang, 2006; Parsons Brinckerhoff, 2012; Staffell & Green, 2013; Sweett Group for DECC, 2013)
Ψ (Fuel cell reformer)	Upfront cost	£	240-3800	717.4	(Battelle, 2014; Daly & Fais, 2014; Körner, 2015)
Ψ (Stirling engine)	Upfront cost	£	750-26500	4193.4	(Daly & Fais, 2014; EPRI Palo Alto CA, 2002; Parsons Brinckerhoff, 2012; Weiss et al., 2010)
$\overline{B}$	Capacity of natural gas boiler	kW	-	30	-
COP_{HP}	Coefficient of Performance of the heat pump	-	2-5.8	3	(Bertsch & Groll, 2008; Kelly & Cockroft, 2011; Y. Tong, Kozai, Nishioka, & Ohyama, 2010)
e_{el}	Carbon intensity of electrical grid	kgCO2/kWh	-	0.0753	(National Grid, 2015)
e_{gas}	Carbon intensity of natural gas	kgCO2/kWh	-	0.1840	(BEIS, 2016a)

L (All heating options)	Lifespan	years	10-15	15	(International Energy Agency, 2010; Orr, 2012; Parsons Brinckerhoff, 2012)
$\overline{P^{EH}}$	Capacity of resistive heater	kW	-	3.5	-
$\overline{P^{HP}}$	Capacity of heat pump	kW	-	27	-
$\overline{P^{el}}$	Electrical capacity of CHP unit	kW	-	1	-
r	Discount rate	%	-	3	-
$\overline{S}$	Capacity of thermal energy storage	kWh	-	5	-
w	Sample weights of representative days	Days	-	[91;91; 91;92]	-

Appendix B – Sample Day Selection Algorithm

This section describes how the typical days were selected. Three parameters drive the selection process: coincidence, thermal demand and electrical demand. Instantaneous coincidence for the current time period is defined as the lower value when comparing electrical and thermal demand. The algorithm makes use of the sum of all instantaneous coincidence values in a day. While thermal and electrical demand values are expected indices for sample day selection, coincidence is not. This is done because coincidence of electrical and thermal demand is a deciding factor for micro cogeneration performance. This parameter determines the savings that can be gained via the combined production of heat and power. The following steps are repeated for every season.

Sequence	Description
Step 1	Calculate sum of all instantaneous values for each day for the three parameters mentioned: coincidence, thermal demand and electrical demand. This provides us with a total value for each parameter in each day of sample data.
Step 2	Calculate the mean of the total values for all days. This overall mean is calculated for all three parameters.
Step 3	Calculate relative deviation of total values for each day from the overall mean. Relative deviation for each day = (Day total – Overall mean)/(Overall mean) Again this is done for all three parameters.
Step 4	An error value is assigned to each day. This error is the sum of relative deviations for the three parameters.
Step 5	Pick the day with the least error value.

Appendix C – Generation Technologies

Electric power has become a crucial requirement for human well-being in developed societies. Its value has extended far beyond the purpose it was initially meant for. Electricity now powers everything from everyday housel hold items like lights, televisions and computers to large industrial equipment used in mills, construction sites and factories.

The electricity grid requires power stations or power plants to convert primary energy into electric power. Primary energy can be derived from conventional or renewable sources. Conventional sources fall into one of three categories: thermal, nuclear and hydroelectric. An illustration of the general working principle is shown in Figure 38. Primary energy is used to rotate the blades of a steam or hydro turbine. The turbine shaft is connected to a generator and AC electricity is generated. Solar and wind are the most widely used renewable sources. Wind sources link up to an AC generator while solar requires an inverter to convert DC into AC before it can be connected to the electricity grid. Each one these alternatives are discussed in greater detail in the sections that follow.

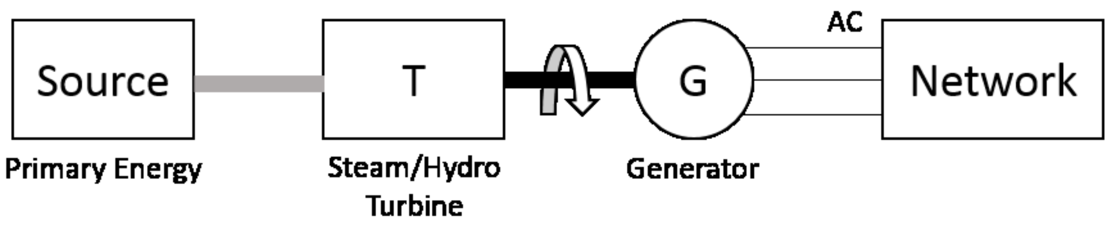

Figure 38 - Conventional power plant operation

Coal Power Plant

Coal is made up of organic matter that was built up millions of years ago and with has turned into fossilised black rock. Power plants usually stock up on coal supplies that can last up to two months. The rocks are finely ground to increase its surface area and hence improve combustion efficiency. As explained earlier, the energy released from the combustion of coal is used to turn a steam turbine which is connected to a generator. The schematic of a coal power plant is shown in Figure 39.

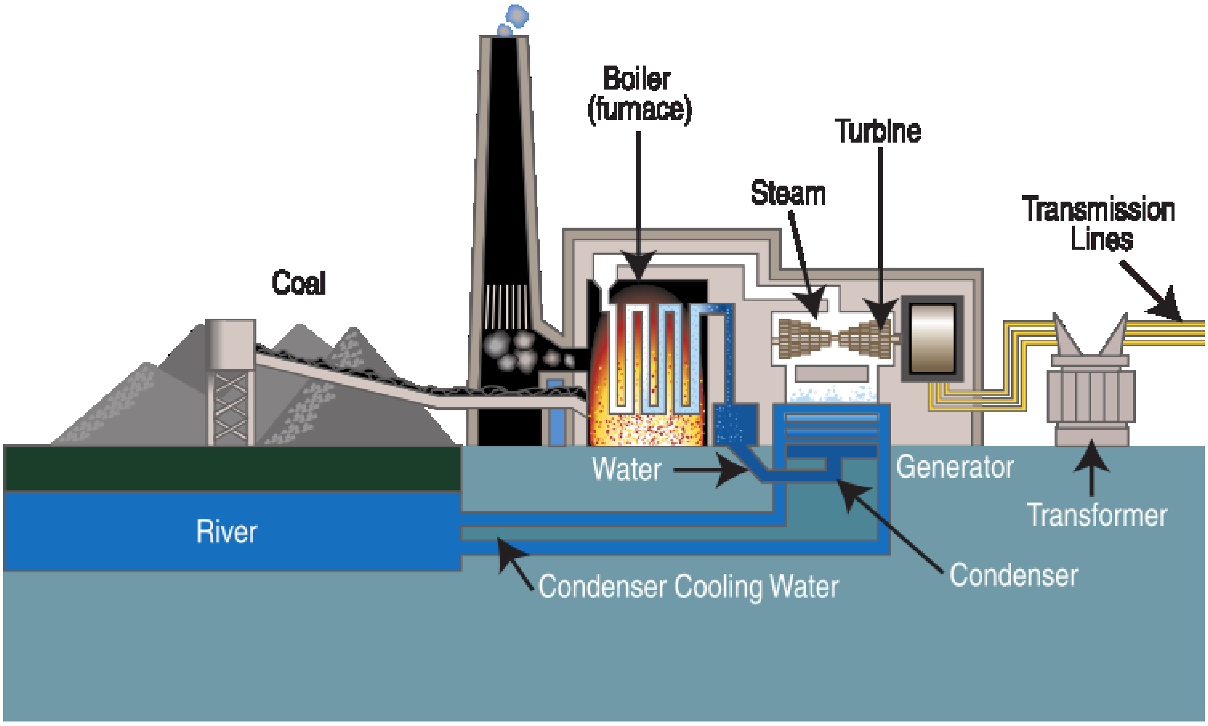

Figure 39 - Schematic of a coal power plant (United States Tennessee Valley Authority, 2013a)

The main components of a coal power plant are: the burner, boiler, tunnel, turbine, condenser and a return channel. Coal is burnt in the boiler to heat water to form high pressure steam. This steam is then transferred to the turbine through a tunnel. The steam then flows through the turbine rotating the shaft that is connected to the generator. The steam then comes in contact with a condenser which cools it down and condenses it to water. In some cases, the heat transferred to the coolant in the condenser (cold water from a nearby source) is released through a cooling tower. This prevents the plant from disturbing the water source (river or water body) which provides the coolant. Finally the condensed water is pumped back into the boiler and the process continues.

Nuclear Power Plant

Nuclear energy can either be derived from fusion or fission. Fusion involves a reaction in which of one type of atom gets converted into another at high temperature and pressure. The fusion of the two nuclei results in an atom at a lower energy state. The difference is released in the form of heat and light. Fusion happens in stars such as the sun where hydrogen atoms combine to form helium. As heavier elements are not easily fused, stars die when they run out of lighter elements. To replicate this reaction on earth requires large amounts of energy input. The amount of energy released in the process is not higher than what was required to start the reaction.

Nuclear fission on the other hand involves the splitting of one heavy atom resulting in lighter ones and a large amount of energy. Modern nuclear fission reactors are able to make this reaction proceed in a controlled fashion. The fuel of choice in such reactors is uranium. Uranium occurs in two forms: U-235 and U-238. The two differ in the number of neutrons. U-238 contains 146 neutrons while U-235 contains 143 neutrons. U-238 is the more stable of the two and is more commonly found in natural deposits of uranium. U-235 is less stable and susceptible to nuclear fission. Less than 0.7 per cent of naturally occurring deposits of uranium are made up of U-235. Enrichment is necessary since these levels need to be increased to 4 per cent before they can be used to generate electricity. Once enriched, they fuel is packed into fuel rods. Nuclear fission can then be amplified through a chain reaction if necessary. These chain reactions propagate in two steps: first is the release of neutrons form the fission of U-235 and subsequent absorption of these neutrons by U-235 in the surrounding medium causing more fission reactions. Nuclear reactors depend on the use of control rods to absorb the neutrons released through fission to control the rate at which the reaction proceeds. These rods are lowered into the reactor to slow down the reaction and are lifted to allow the neutrons to bombard nearby U-235 to increase the rate of the reaction. These control rods are usually made of cadmium or boron. These are housed in a containment structure along with the reactor as shown in Figure 40.

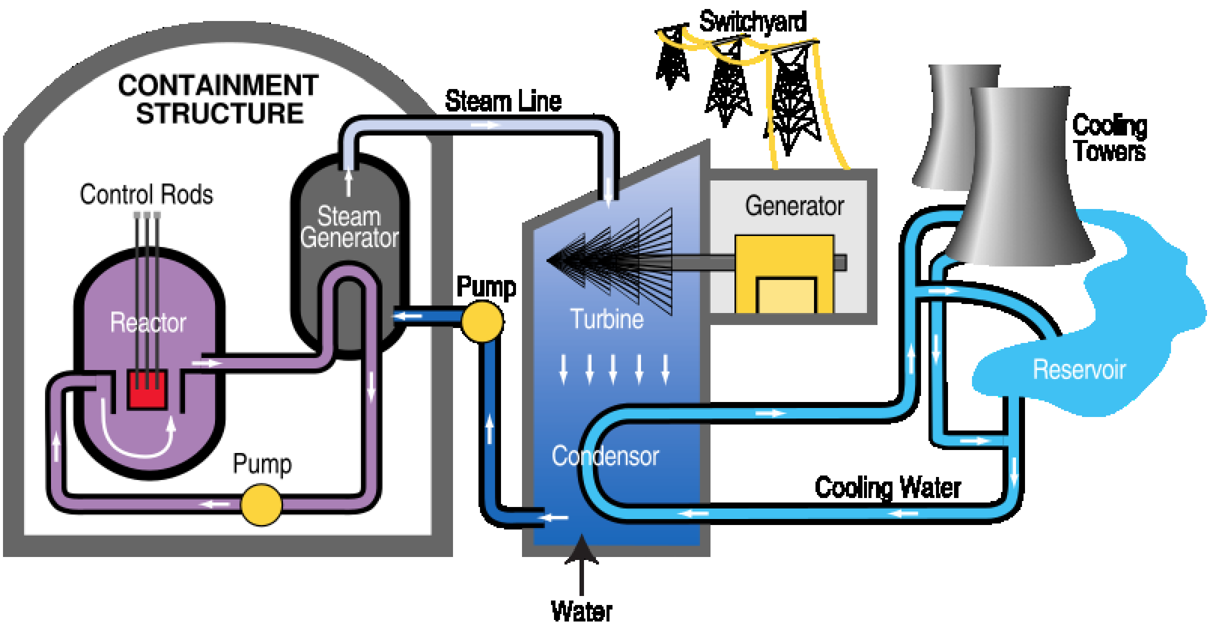

Figure 40 - Schematic of a nuclear power plant (United States Tennessee Valley Authority, 2013c)

Apart from the sections related to the fuel and heat generation a nuclear power plant is similar to a coal power plant since it also makes use of a steam cycle to rotate the shaft of an electric generator.

The pressurised water reactor shown in Figure 40 has a primary and secondary circulation loop. The heat exchanger assumes the role of the boiler in the coal plant. Other elements of operation are similar to coal fired power plants.

Natural Gas Fired Power Plant

Natural gas power plants make use of combustion turbines. The schematic of a combustion turbine is shown in Figure 41. Unlike the previous power plants which made use of steam, air is the working fluid in combustion turbine. It is first brought to high pressure through the use of a compressor. The compressed air is sprayed with fuel through nozzles. The mixture ignites at pressures of the order of 30 atmospheres and temperatures between 650 degree Celsius and 1650 degree Celsius. The combustion products flow through a turbine where expansion occurs when the air moves from high to low pressure. This is accompanied by rotation of the turbine blades and hence spinning of the shaft connected to the generator. One of the aspects not shown in Figure 41 is a motor which is used to run the compressor before the turbine is able perform that function. If this motor were not present the pressure would not be high enough and the air would blow out through the intake itself.

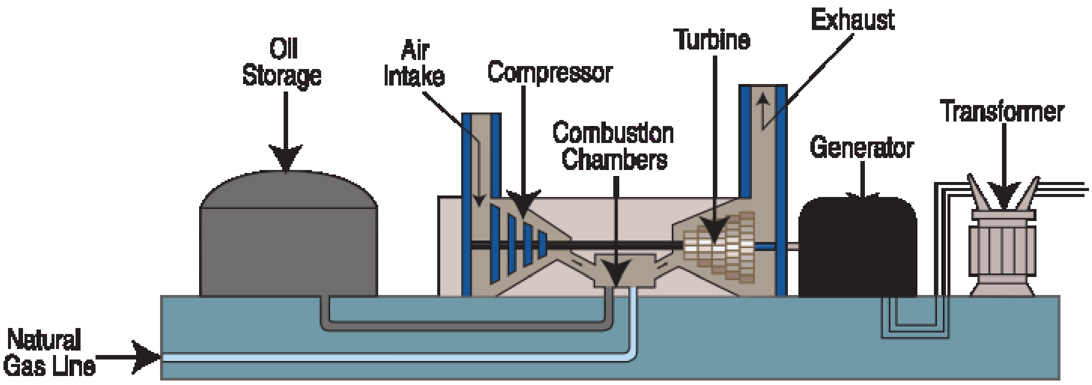

Figure 41 - Schematic of an open cycle gas turbine (United States Tennessee Valley Authority, 2013b)

Combined cycle gas turbines shown in Figure 42 are the result of efforts to improve the efficiency of combustion turbines. The temperature of the air at the exhaust of an open cycle gas turbine is still considerably high. Useful work can be extracted from this source either for the generation of electricity or for other industrial purposes. After serving a gas turbine the air at the exhaust is around 800 degree Celsius. This enters a heat recovery steam generator which acts as a boiler for a separate steam cycle. Water is converted into steam which is directed through a second turbine and generator set. This modification increases the efficiency from 32 per cent to 53 per cent.

The main difference between the gas turbine and a steam turbine is the lower start-up time. Gas turbines can be started within 10 minutes of commencing operation while steam turbines take hours to heat up the boiler. This makes them an ideal choice for providing reserves.

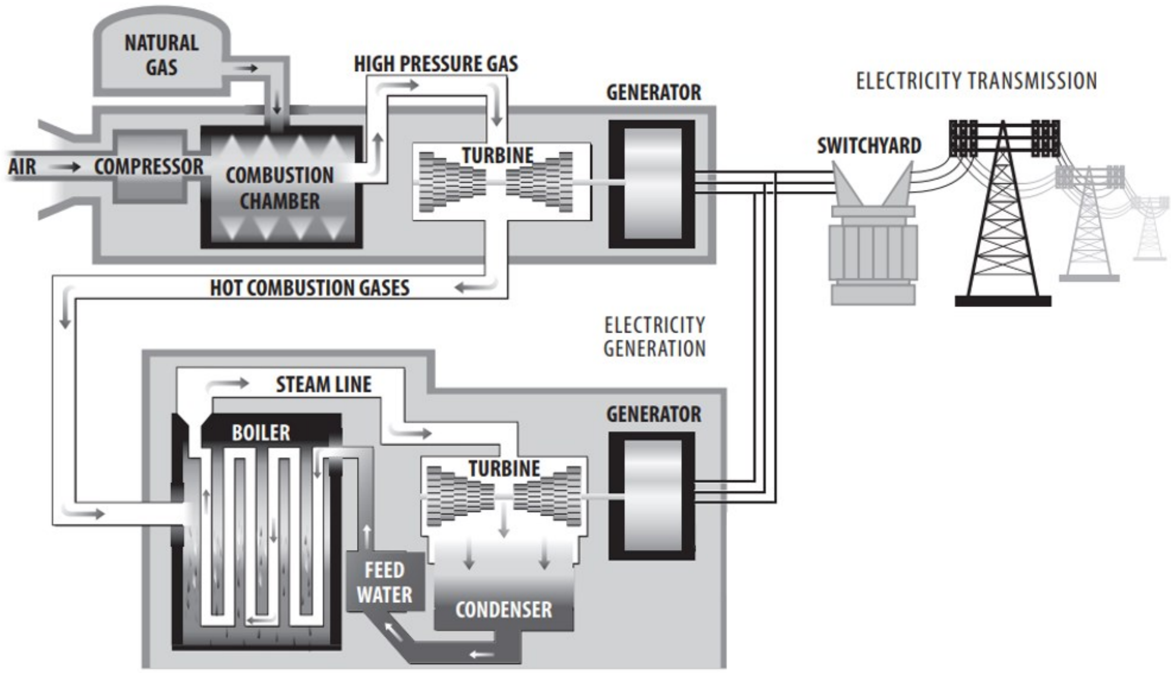

Figure 42 - Schematic of a combined cycle gas turbine (NEED, 2015)

Hydroelectric Power Plant

Hydroelectric power plants channel water through a turbine to generate electricity. This can be done through the use of a dam which arrests the flow of a water body or by letting the natural flow of water pass through a turbine or by pumping water from a low lying reservoir to an elevated reservoir to be released at a later point. Each one corresponds to a different type of hydroelectric plant as described below.

Hydroelectric power plants have much higher efficiencies in comparison to fossil fuelled power plants. This is because hydroelectric power is devoid of wasteful exhausts and conversion losses associated with converting of water to steam. Losses are limited to mechanical losses in the turbine, frictional losses due to the viscosity of water and the losses in the generator. Large hydroelectric power plants build dams to capitalise on the height difference between the water surface and the turbine as shown in Figure 43. The penstock connects the reservoir to the turbine. These turbines are usually fitted with valves that can control the flow rate from the reservoir. With the combination of these valves and gates that divert water towards or away from the turbine, the output can be modulated faster than other technologies. This makes them an ideal choice for providing balancing services which respond to changes in supply and demand.

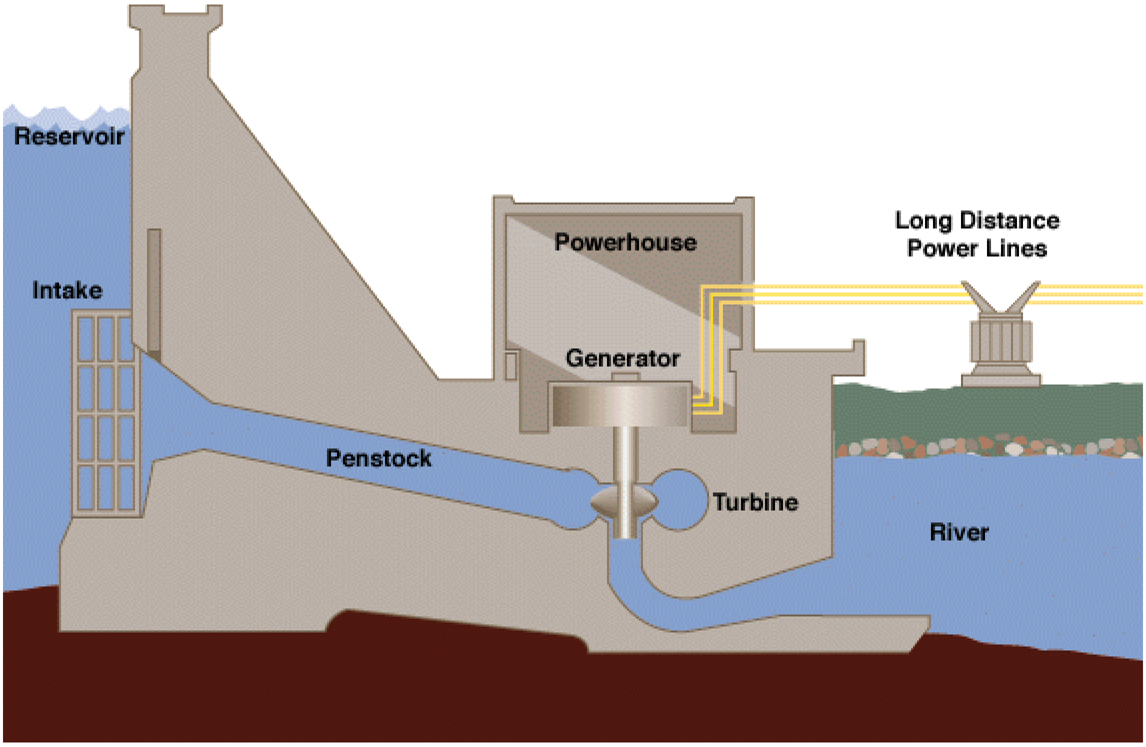

Figure 43 - Hydroelectric dam (United States Tennessee Valley Authority, 2005)

Run of river hydroelectric power involves tapping into the natural flow of water through rivers. This does not necessarily need to involve a difference in height. Since it is mainly found in areas that do not have water storage, output is driven by the natural changes in flow rate. This means that output cannot be controlled and does decline when the flow of water subsides.

Another form of pumped storage is meant to capitalize on the inherent variability of load conditions. Thermal plants come under stress when subject to frequent starting and stopping. Since this can reduce their lifespan, a form of storage to combat this issue is necessary. Pumped storage hydro provides a practical solution to this problem. Its operation is based on the variation of electricity prices. When the generation is greater than the system load, supply is greater than demand resulting in lower electricity prices. This usually happens at night. Water is pumped from a low lying water body to an elevated reservoir. When the demand is greater than supply during the day, the water is released to supply power to the grid. Pumped storage plants gain the highest revenue during periods of peak demand when the electricity prices are the highest. The schematic of a pumped storage plant is shown in Figure 44. The main components in this schematic are the reversible pump-turbine/motor-generator assemblies which are housed in the power plant chamber in Figure 44. These assemblies are the crucial components which differentiate a pumped storage plant from a hydroelectric dam. The surge chamber is meant to absorb sudden rises in pressure as well as make up for a drop in pressure by providing additional water. The transformer vault houses the power transformers. Circuit breakers are present between the generator and the transformer so that the connection can be interrupted in case of short circuits.

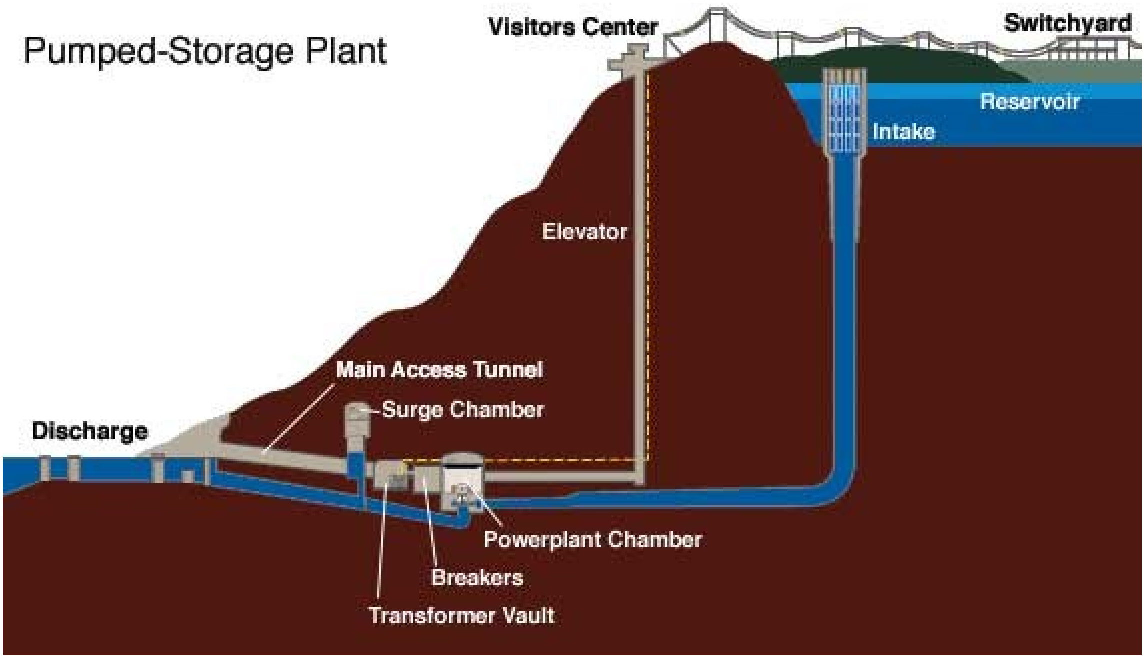

Figure 44 - Pumped storage plant (United States Tennessee Valley Authority, 2004)

The following sections are devoted to renewable sources, namely wind and solar. Such sources do not depend on fossil fuel and do not emit gases that contribute to global warming and are hence seen to be major instruments that can combat climate change.

Wind Power Plant

The ultimate source of wind energy, as with other sources, is the sun. The sun heats up a certain portion of land which heats up the air around it. When sufficiently heated, hot air begins to rise as a given volume of hot air is lighter than the same volume of cold air. As the hot air rises, cold rushes to fill the gap left behind. This is what we experience as the wind.

Wind power plants also make use of turbines to generate electricity. When a wind turbine is placed in the path of the wind, it pushes against the blades transferring some of its kinetic energy onto the blades. Thus the wind rotates the turbine whose shaft is coupled with a generator which produces electricity. The simplest wind turbines consist of rotor blades, a shaft a gear box and a generator as shown in Figure 45. The gearbox is added to increase the speed of rotation from a low speed rotor to a higher speed electric generator. More advanced variants have safety systems that shut down the wind turbine when the wind speeds are too high.

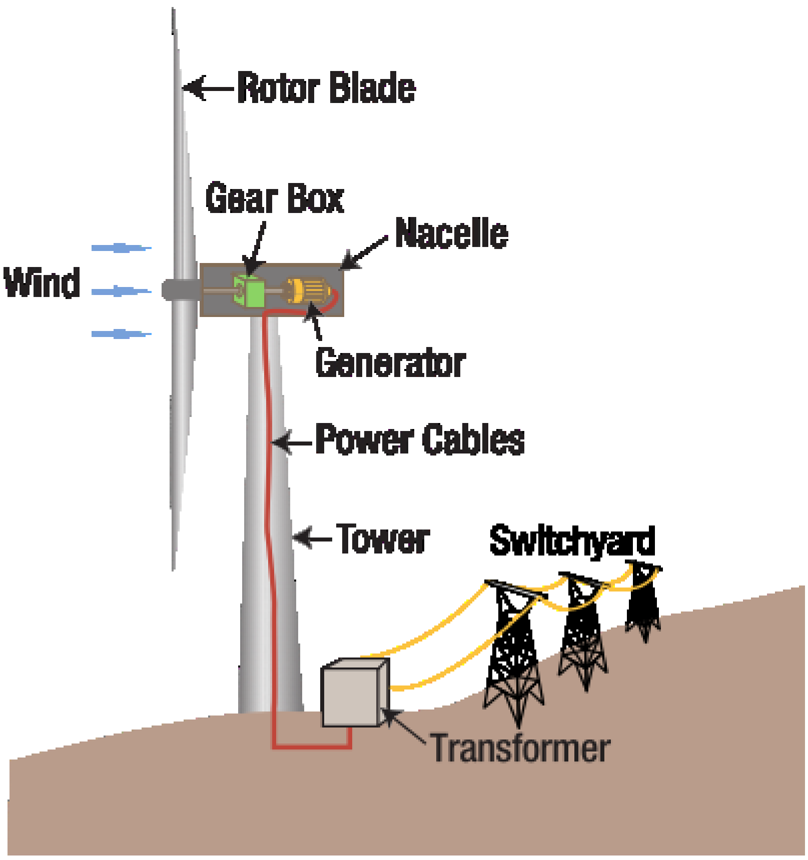

Figure 45 - Schematic of a wind power plant (United States Tennessee Valley Authority, 2013e)

Solar Power Plant

Solar cells are also called photovoltaic cells. Such cells convert light from the sun into electricity. They are usually made of semiconductor materials such as silicon. When sunlight strikes the cell it is absorbed by the semiconductor material knocking an electron loose from its parent atom. This flow of electrons is known as current. The metal contacts on the top and bottom of the solar cell allow us to create an electrical circuit and draw the current to power loads and appliances as shown in Figure 46.

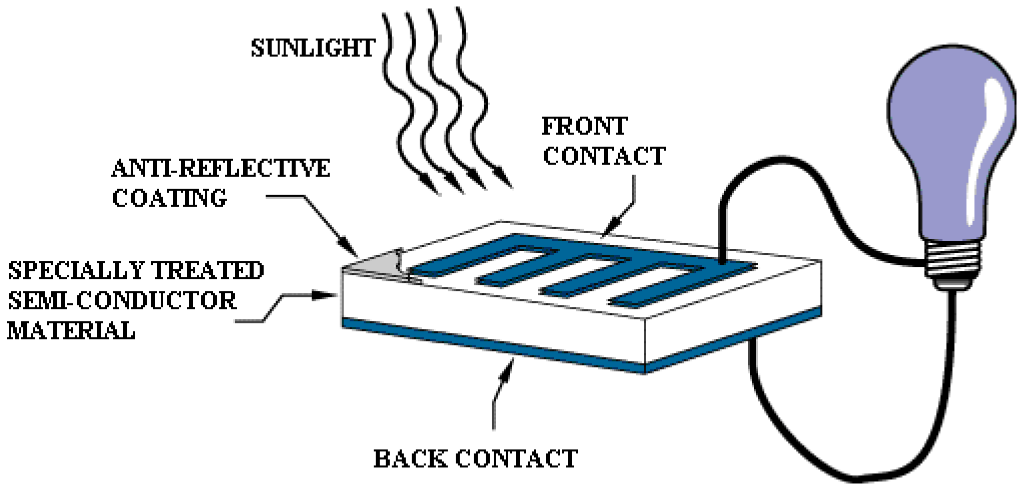

Figure 46 - Operation of a simple solar cell (NASA, 2011)

Many solar cells need to be combined together to harness more sunlight. Grid scale applications require solar arrays. Solar arrays are made up of multiple modules and each module is made up of multiple solar cells. Many such solar arrays make up a solar power plant. Solar panels are a source of DC power. Hence, electrical interfaces are required before they can be connected to the grid. This interface consists of a power electronic inverter and a transformer as shown in Figure 47.

Renewable sources are inherently variable as they are dependent on the wind blowing and the sun shining. Increasing penetration of such sources has an impact on the operation of the electrical grid and hence the electricity prices as discussed in Chapter 3.

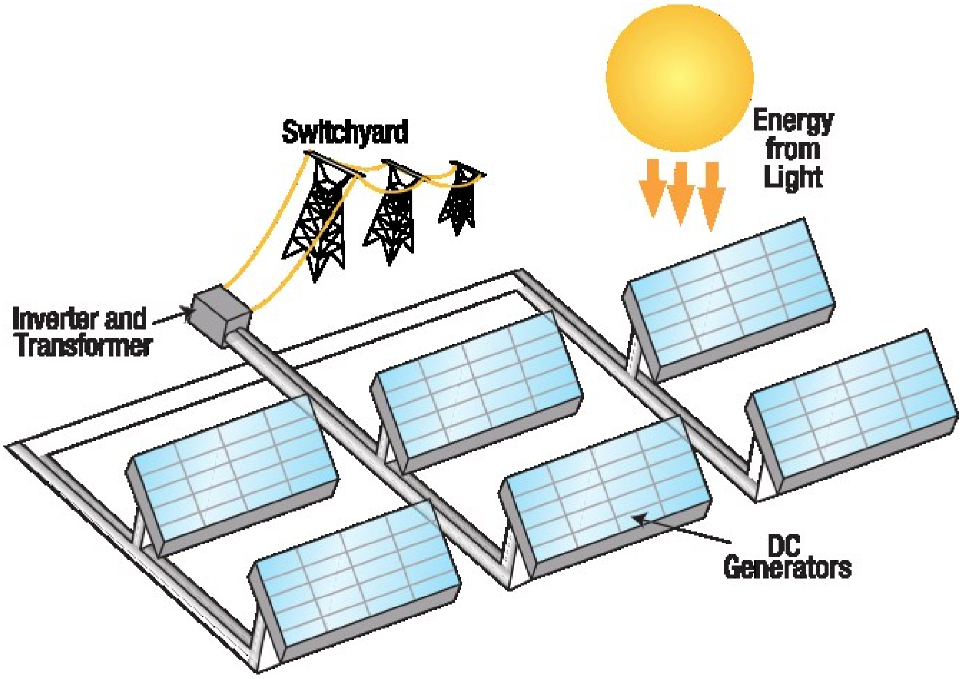

Figure 47 - Schematic of a solar power plant (United States Tennessee Valley Authority, 2013d)

Appendix D – Computational Details

Computer Specifications	
Processor:	Intel(R) Core(TM) i7-2670QM CPU @ 2.20GHz
Installed memory (RAM):	8.00 GB

Power Dispatch Model – One Sample Day

Model Statistics	
Blocks of equations	23
Blocks of variables	17
Non zero elements	166,294
Single equations	60,731
Single variables	54,145
Discrete variables	20,256
Solver	
Name:	IBM ILOG CPLEX
Version:	12.6.0.0
Solution Details	
Status:	Normal completion
Elapsed time:	3.9 seconds

Residential Heating System – Micro Cogeneration – One Sample Day

Model Statistics	
Blocks of equations	21
Blocks of variables	19
Non zero elements	11,236
Single equations	4,612
Single variables	4,324
Discrete variables	1.152
Solver	
Name:	IBM ILOG CPLEX
Version:	12.6.0.0
Solution Details	
Status:	Normal completion
Elapsed time:	0.5 seconds

Dynamics of Fuel Cell based Micro Cogeneration – One Sample Day

Model Statistics	
Blocks of equations	29
Blocks of variables	22
Non zero elements	18,691
Single equations	6,340
Single variables	5.188
Discrete variables	2,016
Solver	
Name:	IBM ILOG CPLEX
Version:	12.6.0.0
Solution Details	
Status:	Normal completion
Elapsed time:	0.7 seconds

Demand Side Flexibility – Micro Cogeneration – One Sample Day

Model Statistics	
Blocks of equations	21
Blocks of variables	19
Non zero elements	11,032
Single equations	4,612
Single variables	4,324
Discrete variables	1.152
Solver	
Name:	IBM ILOG CPLEX
Version:	12.6.0.0
Solution Details	
Status:	Normal completion
Elapsed time:	0.6 seconds