Assessment of Heat Supply Options for Decarbonising Dwellings: Case studies of Cardiff, Swansea and Newport

Alexandre Canet

School of Engineering

Cardiff University

A thesis submitted for the degree of Doctor Of Philosophy

22 June 2021

Acknowledgements

I would like to thank Professor Nick Jenkins, Dr Meysam Qadrdan and Professor Jianzhong Wu for giving me the opportunity to join the CIREGS group and conduct this research. Their comments, guidance and supports were very helpful and resulted in a very rewarding experience.

I would also like to thank all the members of the CIREGS group who provided me with valuable feedbacks over the years. Specially, my gratitude goes to Lahiru, Muditha and Sathsara.

Thank you.

Abstract

Residential heat decarbonisation is a major challenge if the UK is to reach its objective to reduce greenhouse gas emissions under the Paris agreement. To date, the government has focused on national scale plans. However, the viability of heat decarbonisation pathways is also significantly affected by the local circumstances. The same heat supply options installed in one area may not result in the same costs and performance in another area.

To develop local heat decarbonisation pathways, new data and tools need to be developed. In this thesis, several methods and models are described to begin to answer this problem, including:

1. A method for estimating the heat demand of different types of dwellings before and after implementing energy efficiency measures in local areas. Information about the type of dwellings in an area, their heat demand and the heat demand density of the area were derived to assess the heat supply options.
2. Models were developed to synthesise half-hourly heat production and energy consumption of ASHPs, GSHPs, natural gas/hydrogen boilers, resistance heaters and district heating. This was used to understand the timing and height of the peak energy demand of different heating technology, and also to calculate the costs for reinforcing the electricity distribution network and converting the natural gas network to hydrogen or different heat decarbonisation pathways.
3. An optimisation model was used to assess the heat supply options for local areas.

These methods and models were demonstrated in case studies in the cities of Cardiff, Swansea and Newport. The results showed that these local authorities should include a significant amount of individual heat pumps and dwellings connected to district heating by 2050 to decarbonise heat. Hydrogen boilers were not found to be an economically viable option.

CONTENTS

List of Figures

List of Tables

Nomenclature

ADMD: after diversity maximum demand

ASHP: air-source heat pump.

EPC: Energy Performance Certificate that provides details of the energy performance of a property.

COP: Coefficient of performance.

Gas boiler: in this paper gas boiler refers to a boiler that uses natural gas or hydrogen as fuel.

GSHP: ground-source heat pump.

LSOA: Lower layer Super Output Areas that give the boundaries of geographical areas which are used to organise national statistics and census data from the Office for National Statistics. An LSOA has on average 1,614 inhabitants and 672 households. There are 34,753 LSOAs in England and Wales [1].

MSOA: Middle layer Super Output Areas that give the boundaries of geographical areas which are used to organise national statistics and census data from the Office for National Statistics. An MSOA is constituted from several LSOAs. There are in average 4.8 LSOAs in each MSOA, for a total of 7,201 MSOAs in England and Wales[1].

OAT: outside air temperature.

ONS: Office for National Statistics is the office in charge of producing statistics for the UK.

UK: The United Kingdom includes England, Northern Ireland, Wales and Scotland. Great Britain is the UK excluding Northern Ireland.

1 Introduction

1.1 BACKGROUND

No profound changes impacted the UK residential heat demand between 1970 and 2018. Although there were energy efficiency improvements in dwellings and heating systems, the overall heat demand remained similar. In terms of the heat supply options, the share of gas boilers significantly increased and they became the main choice for heating, replacing options based on electricity, solid fuel or oil.

Figure 1-1 shows the space heating and hot water demand for dwellings from 1970 to 2018 in the UK. The decrease in heat demand for hot water is due to energy efficiency improvements (e.g. hot water storage and heating systems), and the greater use of electric showers and dishwashers [2]. The trend for space heating continued to grow until the years 2000, where it started to decrease. This may be explained by a combination of factors, including energy efficiency measures, an increase in energy prices, and changes in building stock and household composition [3]. In total, the heat demand increased by 8% in 2018 compared to 1970 to reach 400 $TWh_{thermal}$.

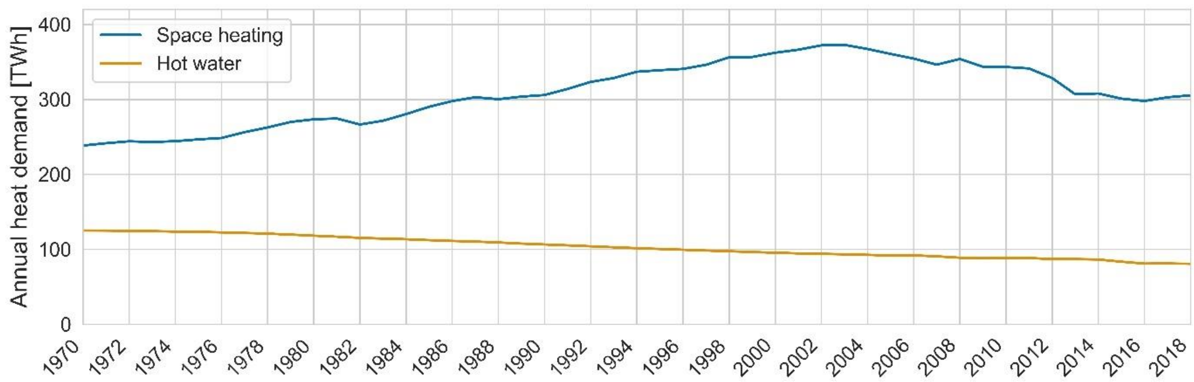


Figure 1-1: Space heating and hot water demand of residential consumers in the UK from 1970 to 2018 (Source: table U3 from [4] using 0.01163 ktoe/TWh as conversion factor)

Figure 1-2 shows some of the factors that explain the overall increase in heat demand in the past three decades despite the improvements in energy efficiency. Figure 1-2.a shows how the improvements of the energy efficiency level of the dwelling stock, as measured using Standard Assessment Procedure (SAP) rating, was negated by an increase in the average indoor temperature between 1970 to 2010. Figure 1-2.b shows how the increase in average indoor temperature was supported by the uptake of central heating in dwellings, which went from being installed in ca. 20% of the dwellings in 1970 to more than 92% in 2018.

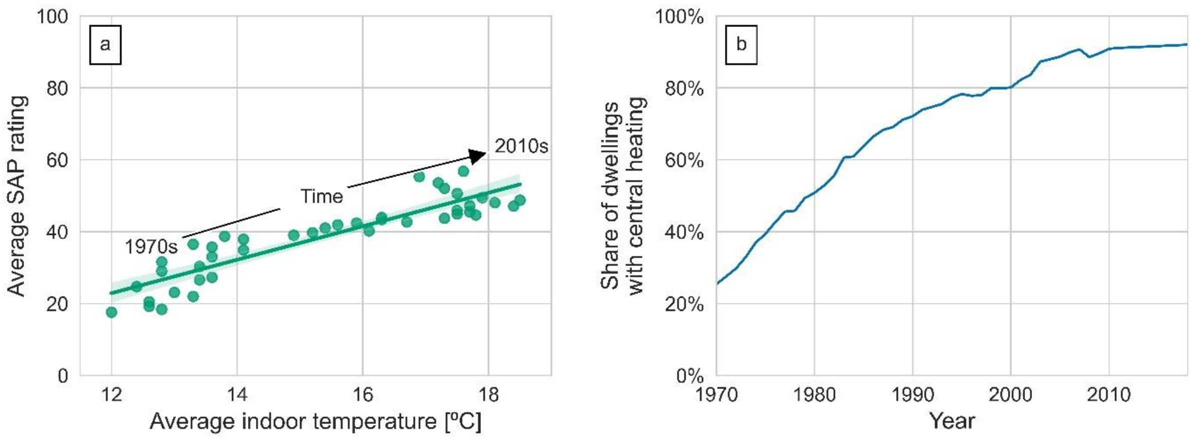


Figure 1-2: Average indoor temperature of dwellings against average SAP (panel a) with data from [4] and [5], the share of dwellings with central heating from 1970 to 2018 in the UK (panel b) [5] and [6].

The residential heat demand has been met by a growing share of natural gas use since the 1970s. Overall, natural gas has provided an affordable way to heat dwellings.

Figure 1-3.a shows the share of heating technologies installed in UK dwellings between 1970 and 2018. This figure shows that the share of natural gas-based heating technologies increased from 40% in 1970 to more than 85% in 2018. There was also a significant decrease in solid fuel heating from 30% in 1970 to almost 6% in 2018. In 2018, more than 90% of the heating systems installed used fossil fuels.

Figure 1-3.b shows the share of different type of gas boilers installed in UK dwellings from 1970 to 2018. In the 1970s, the standard/back boiler was the only technology available. From the 1990s, condensing boilers started to replace standard/back boilers and they reached 70% of the gas boilers installed in 2018. This was achieved through a series of incentives and regulations that started in 1993 [7]. Regarding non-gas-based heating technologies, no significant changes were observed. The uptake of low-carbon heating technologies was still low in 2019, with only 66,317 installations approved under the domestic RHI[1] scheme for the period from April 2014 to January 2019 [8]. This represents less than 0.2% of the dwelling stock of the UK.

[1] The Renewable Heat Incentives (RHI) is a UK Government scheme to encourage the uptake of low carbon heat technologies.

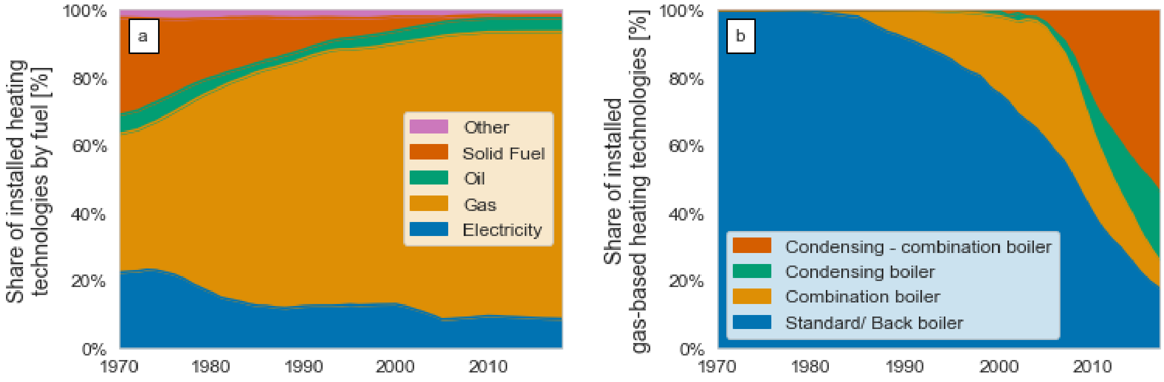


Figure 1-3: Share of heating technologies by fuel installed in UK dwellings between 1970 and 2018 (panel a) [5] and [6]. The "Other" category includes district heating. Breakdown of gas technologies from 1970 to 2018 (panel b), the data from 1975 was backcasted to 1970 [4].

Figure 1-4 shows the carbon emissions by heating fuels from 1970 to 2018. Despite the increase by 8% of the total heat demand between 1970 and 2018 (from 372 TWh in 1970 to 397 TWh in 2018), the carbon emissions decreased by 35% in the same period. This represents a decrease of the carbon intensity of heat from ca. 320 gCO_2e/kWh to ca. 200 gCO_2e/kWh, which is similar to the carbon intensity of heating with condensing gas boilers [9].

The Committee on Climate Change (CCC) advised a 70% to 95% emission reduction target by 2035 compared to the 1990 level for the residential heat sector for the sixth carbon budget[2] from the CCC [10].

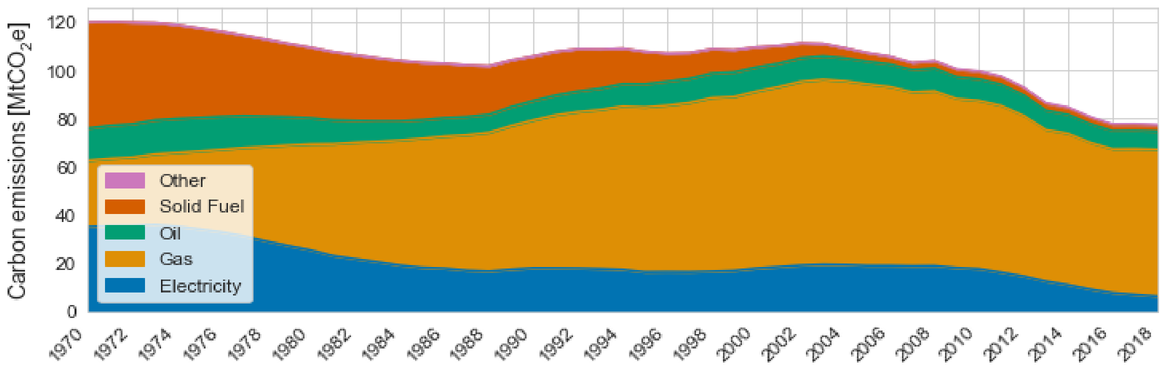


Figure 1-4: Carbon emissions by heating fuels from the residential heat sector from 1970 to 2018. The carbon intensity of electricity was calculated from BEIS data [11].

[2] The sixth carbon budget sets the legal limit for UK net emissions of greenhouse gases for the period 2033-2037.

1.2 CHALLENGES OF DECARBONISING THE RESIDENTIAL HEATING SECTOR

In 2019, the UK amended its previous target of an 80% reduction in CO_2 emission by 2050 (compared to the 1990 level) to achieve a net-zero economy by 2050. According to the CCC [12], this means that 90% of the UK's dwellings will be required to have low-carbon heating by 2050. As an intermediate target, the carbon intensity of 180 $gCO_{2eq}/kWh_{thermal}$ by 2030 was suggested for producing residential heat [13]. In contrast to electrical power supplies, which are being decarbonised rapidly, the residential heat sector has failed to achieve the same level of success.

Some of the key challenges faced in the heat decarbonisation of the residential sector by 2050 include the following:

- The residential heat sector is dependent on fossil fuels for more than 90% of the installations, with a current average carbon intensity of heat above 200 gCO2e/kWh in 2018.
- The residential heat sector is dominated by natural gas boilers, with no significant uptake of any low-carbon technology to replace them.
- Difficulty in reducing the heat demand, despite improvements in the energy efficiency of dwellings.
- Short timeline to replace fossil-fuel based heating systems with low-carbon heating systems, it took almost 20 years for condensing gas boilers to replace almost all standard boilers after the first incentives and regulations.

1.3 STRUCTURE OF THIS THESIS

This research aimed to develop tools and produce data to study the challenge of heat decarbonisation of the residential sector in local areas by considering their characteristics and the national target. **Three local authorities located in South Wales, UK were chosen as case studies: Cardiff, Swansea, and Newport.** Figure 1-5 shows the location of these three local authorities in Wales.

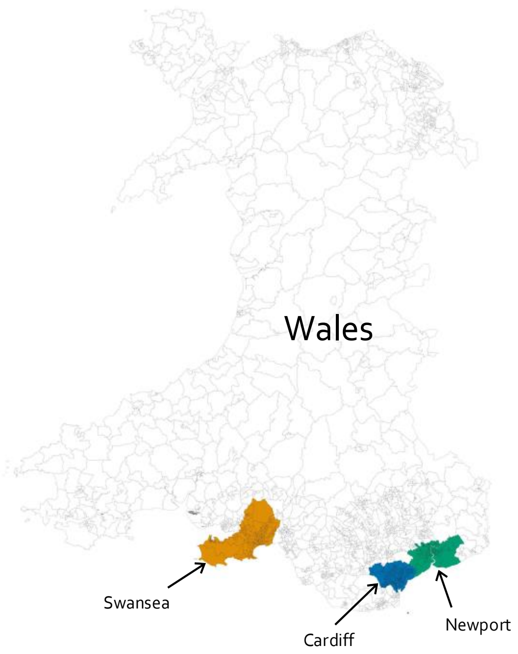


Figure 1-5: Map of Wales showing the case studies in Cardiff, Swansea and Newport

The overall structure of the thesis is shown in Figure 1-6 . This thesis has eight chapters, as follows:

- Chapter 2 reviews the literature of the heat decarbonisation pathways for the UK and Wales, as well as the methods to estimate annual heat demand, synthesise heat profiles, and the modelling tools for heat planning.
- Chapter 3 describes the method to estimate the annual heat demand of different types of dwelling at the local level before and after energy efficiency improvements. This estimate was used to estimate the heat demand for Cardiff, Swansea and Newport in 2018.
- Chapter 4 describes the models that were used to synthesise half-hourly heat production and energy consumption of air-source heat pumps, ground source heat pumps, resistance heaters, gas/hydrogen boilers, and district heating. Two heat decarbonisation pathways for 2050 for Cardiff, Swansea and Newport were defined and their half-hourly profiles were produced using these models.
- Chapter 5 estimates the half-hourly peak electricity demand for heating in the two heat decarbonisation pathways.
- Chapter 6 describes a model to assess local heat supply options in local areas, which includes a formulation of the objective function of the model and its characteristics. Neath Port Talbot was used as an example to demonstrate this new model [14].

- Chapter 7 describes how the methods and models from Chapters 3 to 6 were used to develop heat decarbonisation pathways for Cardiff, Swansea and Newport using cost analysis.
- Chapter 8 draws a conclusion, describes the limitations, and makes some recommendations for further research.

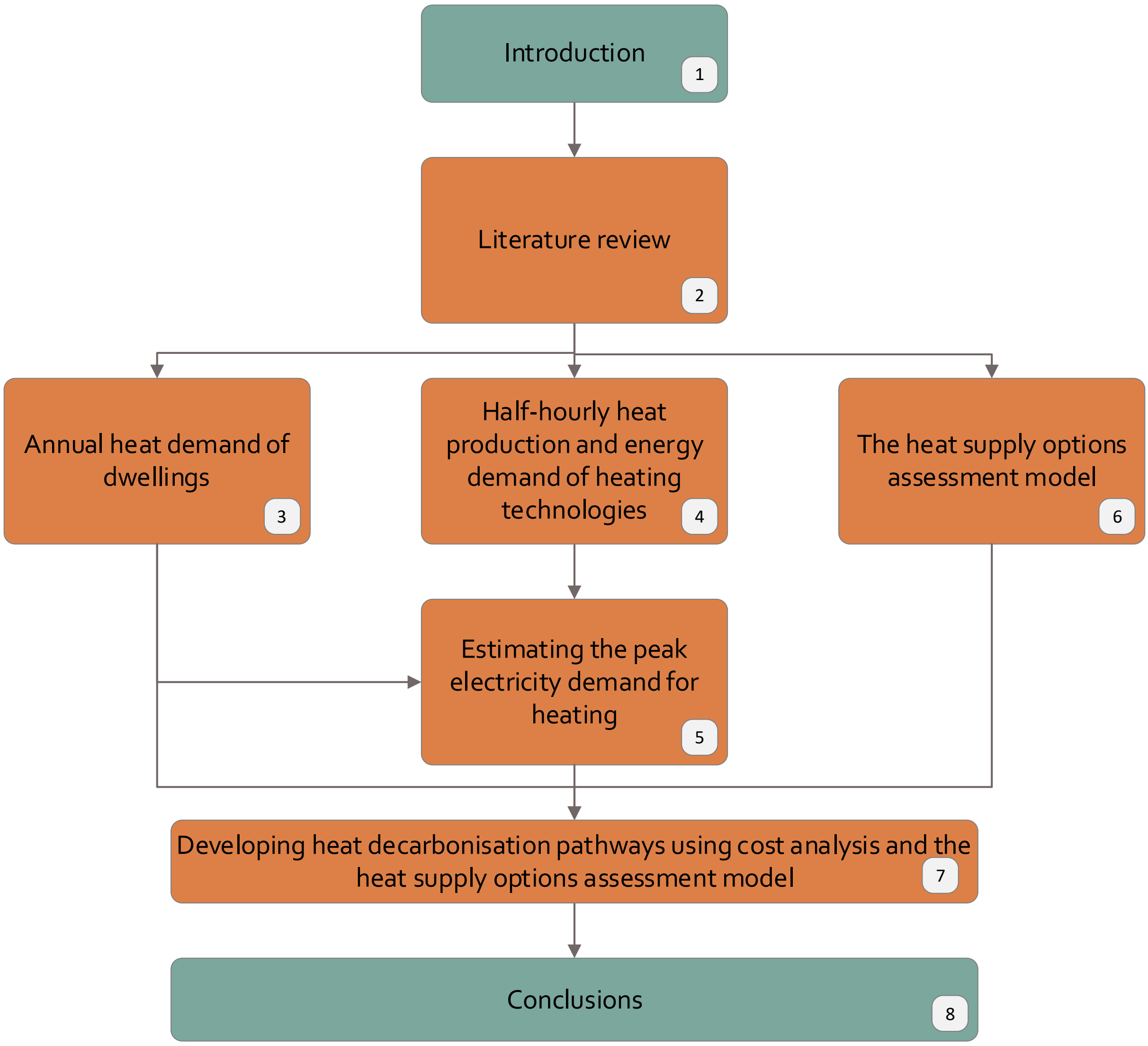


Figure 1-6: Structure of this thesis

1.4 KEY CONTRIBUTIONS AND ACHIEVEMENTS

Part of the work in this thesis was used to produce deliverables for the zero2050 project. The zero2050 project was led by National Grid (www.zero2050.co.uk/) and looked at ways to achieve carbon neutrality[3] in South Wales across all sectors by 2050.

Dr Meysam Qadrdan and myself were responsible for the work package, which used the following outputs from this thesis:

- Producing a baseline of the residential heat demand in Cardiff, Swansea and Newport in 2018, and projecting their values for 2030, 2040 and 2050. It included a breakdown of annual heat demand for different dwelling categories.
- Defining two heat decarbonisation pathways for South Wales.
- Synthesising half-hourly heat production and energy consumption for these three local authorities for the two heat decarbonisation pathways for 2030, 2040 and 2050.
- Estimating the peak electricity demand for heating in all scenarios.

Other contributions include the publication of the following papers:

- Canet, A., Qadrdan, M. and Jenkins, N. 2021. Heat demand mapping and assessment of heat supply options for local areas – the case study of Neath Port Talbot. Energy 217, article number: 119298. (10.1016/j.energy.2020.119298)
- Seward, W., Canet, A. and Qadrdan, M. 2020. Spatially explicit scenarios for decarbonising heat in domestic buildings. Presented at: 55th International Universities Power Engineering Conference (UPEC 2020), Virtual - Torino, Italy, 1-4 September 20202020 55th International Universities Power Engineering Conference (UPEC). IEEE pp. 1-6., (10.1109/UPEC49904.2020.9209775)
- Database of the annual heat demand for 16 dwelling categories at LSOA level for England and Wales (on-going). The data is available on the UKERC website at the address https://doi.org/10.5286/ukerc.edc.000944. The journal article describing the methodology used is being reviewed at the time of this PhD.

[3] CO_2 neutrality refers to the balance between the emissions of greenhouse gases and their removal from the atmosphere.

2 Literature Review

2.1 Introduction

The final energy demand for space heating and domestic hot water in the UK domestic sector in 2018 was close to 400 $TWh_{thermal}$, which was supplied by natural gas at 84% [4]. Given the time pressure to reach the 2050 target for carbon neutrality, a large number of reports and analyses have aimed to describe heat decarbonisation pathways while focusing on a range of heat supply options. In this section, the heat decarbonisation pathways for the UK and Wales will be reviewed. Methods to estimate heat demand, synthesise heat demand profiles and the modelling tools for heat planning that are used in the literature to develop and study the impacts of heat decarbonisation pathways will also be described to identify any gaps and challenges in the literature.

2.2 Heat Decarbonisation Strategies

2.2.1 Heat Decarbonisation Strategies in the United Kingdom

The heat decarbonisation pathways that were published before the announcement of the GB's contribution to carbon neutrality by 2050 (27 June 2019) [15] were often not compatible with this new target. In 2015, Chaudry et al. [16] reviewed the UK heat decarbonisation pathways that were compatible with the previous target (80% carbon emissions reduction by 2050) to study the uncertainties surrounding heat decarbonisation. Although some pathways would come close to carbon neutrality, such as the electrification pathways produced by Delta-EE in 2012 [17] that reached a 96% reduction compared to the 2010 level, they all still predict some use of fossil fuels for heating by 2050.

The carbon-neutral pathways from the three sources that are described in this section cover a range of different heat supply options, including 11 pathways from the Future Energy Scenarios 2020 (FES) [18], the "development of trajectories for residential heat decarbonisation to inform the sixth carbon budget" by Element Energy (EE) [19] and the "analysis of alternative UK heat decarbonisation pathways" from Imperial College for the CCC [20]. Although these three sources had different scopes, they all included the residential heat sector: the FES looked at the whole system, while EE and CCC focused on residential heat.

Table 2-1 describes the characteristics of the 11 pathways studied in this section. Overall, the 11 heat decarbonisation pathways fell into three main categories, as follows:

- *Electrification pathways*, which assume a large share of electricity-based heating technologies (e.g., heat pumps and resistance heaters).
- *Hydrogen pathways*, which assume that a large share of the dwellings that are currently connected to the natural gas grid will be using hydrogen.
- *Hybrid pathways*, which are more balanced pathways where the choice of the main energy source for heat can change to conduct some arbitrage, overcome extreme events (e.g., cold temperature spells) and/or provide a solution to start decarbonising heat without choosing between electrification and hydrogen pathways.

A description of each of these heating technologies is available in Appendix A.

Table 2-1: List of the main heat decarbonisation pathways described in this study. The category of each pathway is also included: Electrification (E), Hydrogen (H2) and Hybrid (H).

Pathways	Description	Category	Source
EE BP	Balanced pathway (BP) with a high level of electrification from Element Energy report [19].	E	Element Energy for BEIS
EE T	Tailwind (T) pathway shows significant behaviour changes with a high level of innovation to achieve carbon neutrality before 2050 [19].	H	Element Energy for BEIS
EE WE	Widespread engagement (WE) assumes that there will be a high number of changes in people's behaviour resulting in significant demand reduction [19].	E	Element Energy for BEIS
EE H	The headwinds (H) pathway shows slow changes in behaviour and technologies to rely on hydrogen and CCS [19].	H	Element Energy for BEIS
EE WI	Widespread innovation (WI) involves the development of carbon mitigation technologies and measures, which lead to a decrease in cost and a higher level of electrification [19].	E	Element Energy for BEIS

Pathways	Description	Category	Source
FES20 ST	System transformation (ST) relies on hydrogen for heating, similar to EE H [18].	H2	National Grid ESO
FES20 CT	Consumer transformation (CT) shows a high share of electrified heating and a change in consumer behaviour [18].	E	National Grid ESO
FES20 LTW	Leading the way (LTW) represents a fast decarbonisation pathway with a mix of hydrogen and electrification for heating [18].	H2	National Grid ESO
CCC H2	Hydrogen (H2) pathway shows a more extreme hydrogen pathway than EE H and FES ST with almost 80% of the heat supplied through it [20].	H2	Imperial College for the CCC
CCC Electric	Electrification pathway relies on individual heat pumps. It is similar to EE WE from a technology uptake point of view [20].	E	Imperial College for the CCC
CCC Hybrid	Hybrid uses hybrid heat pumps supported by hydrogen boilers in most of the gas grid connected dwellings [20].	H	Imperial College for the CCC

The EE pathways represent a range of possible futures where the carbon emissions target is met. Each pathway has a set of assumptions regarding the change in people's behaviour and the level of technological innovation. Detailed information regarding the type and number of energy efficiency measures implemented is provided across all of the EE pathways. The authors found that these measures combined with behavioural change should decrease heat demand by 11 to 22%.

In FES 2050 published in 2020 [18], four pathways are described but only three are compatible with the carbon emissions target, which are: Consumer Transformation (CT), Leading the Way (LTW) and System Transformation (ST). These three pathways assume that 60% of homes will have an energy performance certificate (EPC) of C or higher by 2035 and that 80% of homes will be off the natural gas grid by 2045. In the ST pathway, a hydrogen grid will be delivering hydrogen to 50% of the dwellings by 2050. The fourth pathway, Steady Progression (SP), does not meet the emissions target and it has a large amount of natural gas still being used for heating and no significant uptake of carbon capture technology by 2050.

The CCC looked at a set of measures that could be applied to reach the 2030 carbon emissions targets in its report 'Next Steps for UK Heat Policy'. All of these measures are considered to be 'low regrets' because they are independent of the long-term pathway chosen. In addition to the increase of the energy efficiency requirements for new builds and the retrofitting of the existing stock (15% heat demand savings are estimated to be cost-efficient), the development of low-carbon heat networks for urban areas and heat pumps for buildings not connected to the gas grid are proposed. The sources that have been considered for low-carbon heat networks are waste heat, large-scale heat pumps, geothermal heat and (potentially) hydrogen [21]. The target of the three CCC pathways [20] described in Table 2-1 was heat demand, which is not supplied by the set of 'low regrets' measures that were previously mentioned. This is equivalent to supplying 71% of the remaining households with low-carbon heating technology. This report concludes that CCC Hybrid using heat pumps with gas boilers offers the least-cost solution (<90£ bn/year). In contrast, the CCC H2 has the highest cost (>120 £bn/year). In terms of carbon savings, the CCC Hybrid and CCC Electric pathways offer the best opportunity to reduce carbon use to zero at a reasonable cost.

There are several options in terms of technologies to achieve the 2050 carbon emissions targets for heat decarbonisation in these 11 pathways. Figure 2-1 shows the heat supply mix of the pathways grouped into three categories: electrification, hydrogen and hybrid pathways.

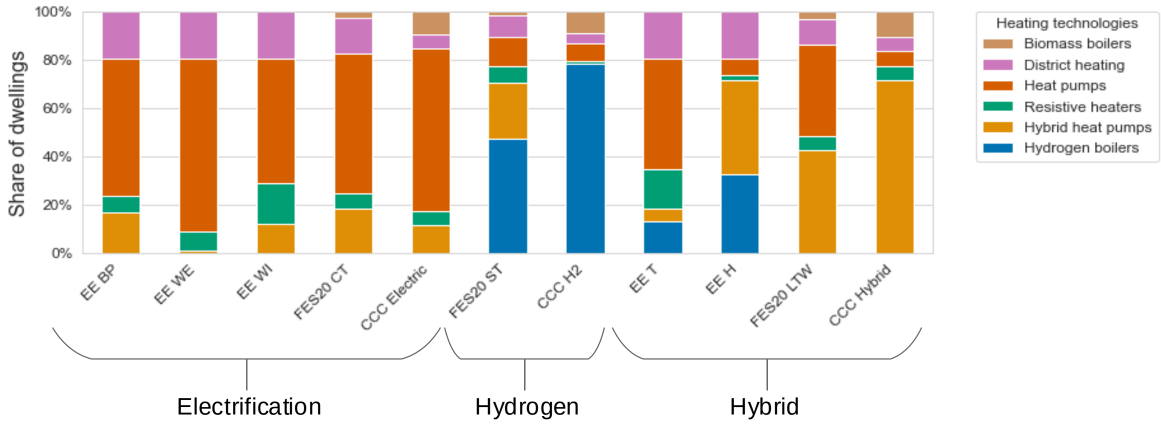


Figure 2-1: Share of dwellings using different heating technologies in the studied pathways in 2050 (source: [19]-[21]).

Heat pumps are a common technology and are available as pure heat pumps (HPs) or hybrid heat pumps (HHPs) in all of the pathways, regardless of the category that they fall into. HPs are mainly installed in dwellings that are not connected to the gas grid to replace carbon-intensive heating systems. This includes dwellings in areas where the gas grid has been decommissioned. Meanwhile, HHPs are mainly based on hydrogen boilers, and thus are installed in dwellings connected to the hydrogen grid. Across all of the pathways, a minimum of 36% of dwellings have heat pumps installed; except in the CCC H2 pathway, where only 8% of the dwellings have heat pumps (less than 1% of the heating systems are currently heat pumps [18]).

District heating also plays a role in all of the pathways, with between 4 to 19% of the dwellings connected to the system (Currently, 2% of the dwellings in the UK are connected to district heating schemes [18]). Although the large development of district heating has been considered, it has been dismissed as a potential solution in the CCC pathways. The large development of district heating within the CCC H2 pathway is found to be significantly more costly than other pathways. For the other pathways, the difference between the original pathway and its equivalent with district heating is around 4 to 5%. This finding may be balanced with the results from other studies. For example, the H2020 project Heat Roadmap Europe developed a pathway for the UK for 2050 by focusing extensively on district heating [22]. Based on their assumptions, which include a 29% heat demand reduction, they find that it is economically viable to have 35% of the heat demand supplied through district heating and 65% of heat demand supplied from individual HPs.

The push for district heating is supported by statistics which show that an increased share of district heating allows for more renewable energy to be used in the heat sector, and thus offers more potential for decarbonisation as seen in Figure 2-2.

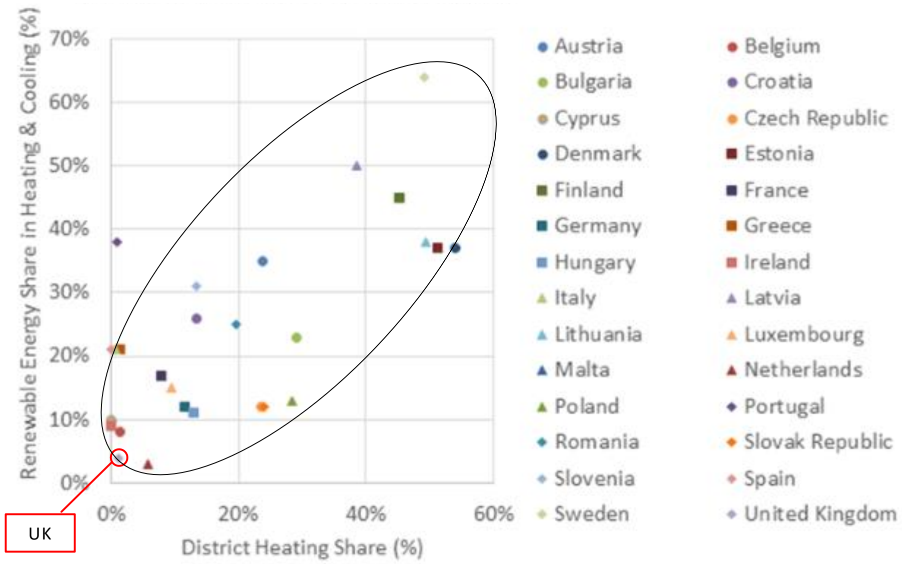


Figure 2-2: Scatter-plot diagram showing the correlation between the share of heat supplied by district heating and the total amount of renewable heat by country (source: figure from [23]).

The heat decarbonisation pathways that are presented here show some of the possible futures for the residential heat sector and the uncertainties associated with them. However, there is no consensus regarding the future heat supply mix and the share of each technology, besides finding that HPs and district heating are likely to be part of the heating mix in the future. One of the common findings from the heat decarbonisation pathways that were reviewed was the requirement for energy efficiency measures.

It is currently unclear how these national pathways would be translated to local areas and if the same findings would be found regarding the choice of heat supply options in each of them. The viability of each decarbonisation option not only depends on their costs and performance but they are also significantly affected by the local circumstances, such as availability of space and level of insulation in buildings, heat demand density in an area [24], the availability of waste heat [25] and existing energy infrastructure (e.g., connection to the gas grid and available capacity in the electricity network) [26].

2.2.2 Heat Decarbonisation Strategies in Wales

Several stakeholders have looked at heat decarbonisation in local areas in Wales, such as Western Power Distribution (WPD) with the distribution future energy scenarios (DFES), and the Welsh Government and National Grid with the zero2050 project. This thesis will present some of the results from the zero2050 project.

In the DFES, WPD describes the implications of the FES pathways for the UK (which are shown in Section 2.2.1) for the distribution network operators (DNOs) area (e.g., South

Wales). However, this report focuses on individual electricity-based technologies and thus contains no information regarding the share of hydrogen boilers installed or district heating by 2050. Figure 2-3 shows the supplied areas by WPD in South-Wales.

The lack of comprehensive studies including other heating technologies may result in lack of planning, risks and missed opportunities for South-Wales.

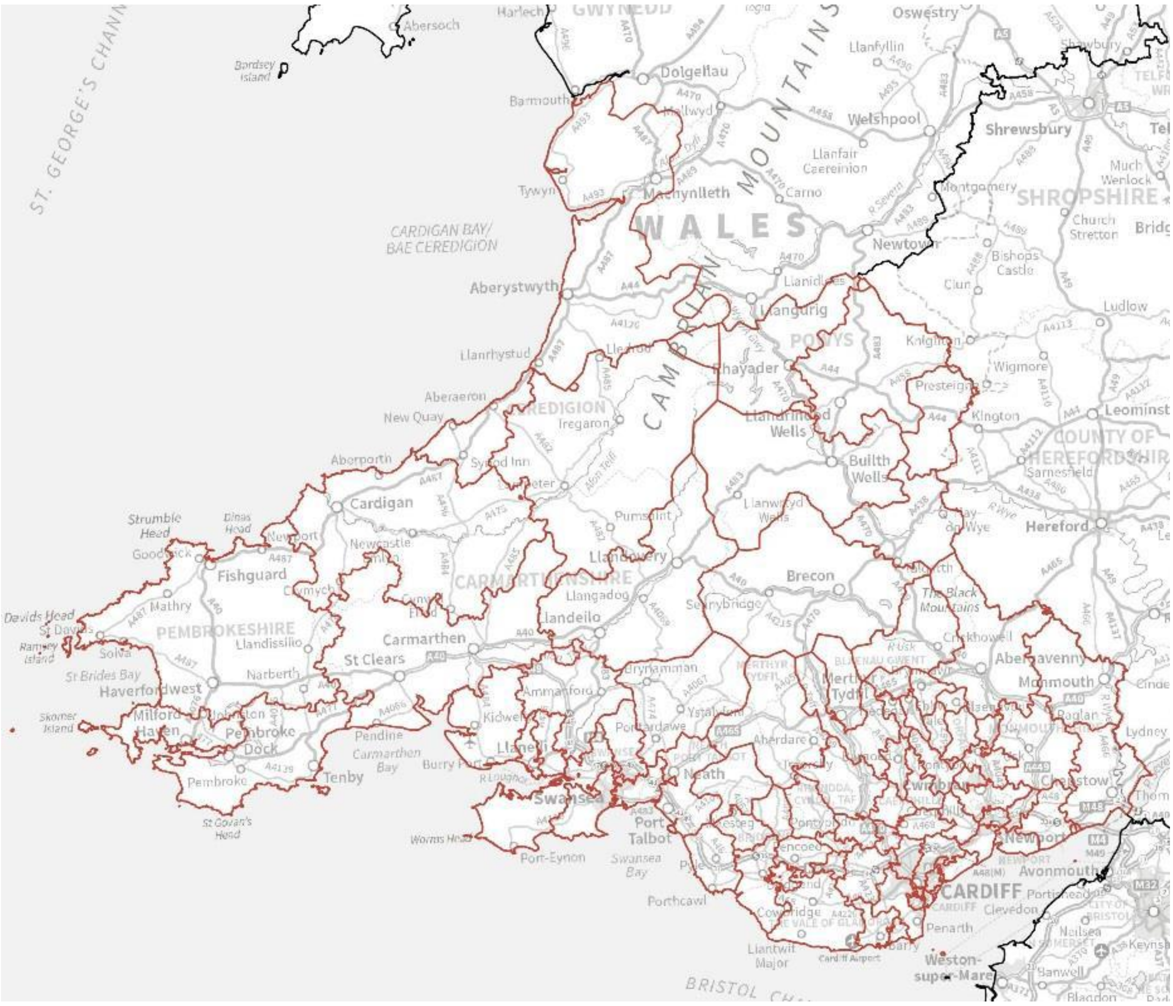


Figure 2-3: Areas supplied by WPD in South Wales are outlined in red (picture from [27])

Figure 2-4 shows the share of dwellings using different heating technologies for the three DFES pathways, which is equivalent to the FES pathways shown in Figure 2-1. The share of HPs in the FES Consumer Transformation (CT) pathways is 58%, and it reaches 64% in the DFES equivalent. Similar observations are made for the Leading The Way (LTW) and System Transformation (ST) pathways. This is explained by a lower share of dwellings connected to the gas grid in South Wales than in the UK. This characteristic also means that there is a lower share of HHPs installed across all of the DFES pathways compared to the national FES pathways.

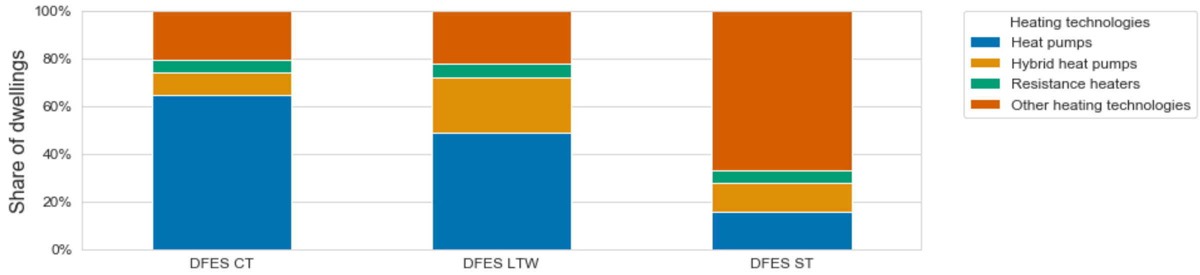


Figure 2-4: Share of dwellings in the DFES pathways for the WPD supply area in South Wales: Consumer Transformation (CT), Leading The Way (LTW) and System Transformation (ST).

The information of the DFES pathways is available for each electricity supply area (ESA) of WPD in South Wales. The ESA areas include all of the customers connected at below 33 kV. While this is helpful from a planning perspective for WPD, it cannot be easily used by other stakeholders because the geographical areas that are used for national statistics are different (e.g., OA, LSOA, or MSOA) or the ESAs are too large.

Figure 2-5 gives a map of Wales that includes the district heating network priority areas that have been identified by the Welsh government [28], this includes most of the large cities. However, no more details are provided regarding where the district heating network may be developed in these cities.

In 2020, there were eight projects in different stages of development in Wales [29], including one in Cardiff using energy from waste and one in Bridgend using mine water.

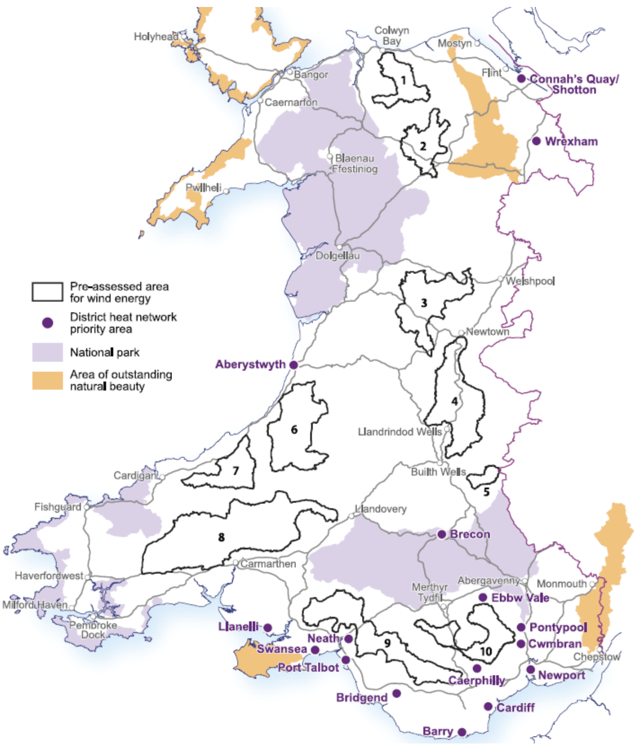


Figure 2-5: Map of Wales with cities identified as a key area for the development of district heating schemes (source: figure from [9]).

There is a growing interest in developing heat decarbonisation in Wales. However, the local authorities do not provide a clear strategy for heat decarbonisation. This includes the 16 local authorities that have declared a climate emergency (7 March 2021). Although most of these local authorities have a target to be carbon neutral by 2030, they all lack a current plan of how to get there. One of the main barriers to the development of these plans is the lack of data, including heat demand data.

2.3 Studies to Estimate Heat Demand

Analysis of local heat supply options requires an estimate of the heat demand from the building stock. However, this is challenging due to the limited amount of measured heat demand data available at fine resolution and the lack of consistent building stock information across different areas.

Several methodologies have been used to estimate heat demand in the UK at different spatial scales. At the national level, Watson *et al.* [30] combined daily aggregate gas demand for the whole GB and data from a trial project to produce a half-hourly heat demand profiles for GB. This method is suitable to estimate aggregate heat demand at the national level due to the large share of gas boilers in GB. However, it is not suitable for estimating heat demand at finer spatial resolution (e.g., local authority, MSOA and LSOA), due to significant variations in the share of heating technologies.

In [31], the authors used gas consumption data, available at the LSOA level [32], to estimate the domestic heat demand. This method provides a good approximation of the heat demand for those LSOAs in which gas boilers are the dominant heating technology.

An alternative approach is presented in [33], which combines building stock information from the Ordnance Survey [34], EPC data and a modelling approach derived from SAP to estimate heat demand at the LSOA level. However, this methodology requires extensive use of geospatial software and was shown not to be very accurate when compared with published data by BEIS [32].

As part of the Heat Roadmap Europe project, Moller et al. [35] developed a pan-European atlas of heat demand with a grid of 100x100m cells. For each cell, the national heat demand for each country was distributed based on quantitative mapping using geospatial methods and an extrapolation of the characteristics of the Danish building stock. This approach has the advantages of providing heat demand at fine spatial resolution and being replicable in other countries. However, it does not offer a detailed representation of the building stock, which could impact the outcomes of the model, and it is difficult to overlay the findings of this study onto UK geographic areas (i.e., LSOAs).

Figure 2-6 gives a summary of the characteristics of these methods based on the resolution of the heat demand data and the details of the building stock model that can be developed from it. Top-down approaches are used to produce the heat decarbonisation pathways presented in Section 2.2.1. Heat demand may be represented by a single number or by a simple building stock model. Meanwhile, bottom-up approaches are used for studies where the change in accuracy or better representation of the building stock may lead to different outcomes.

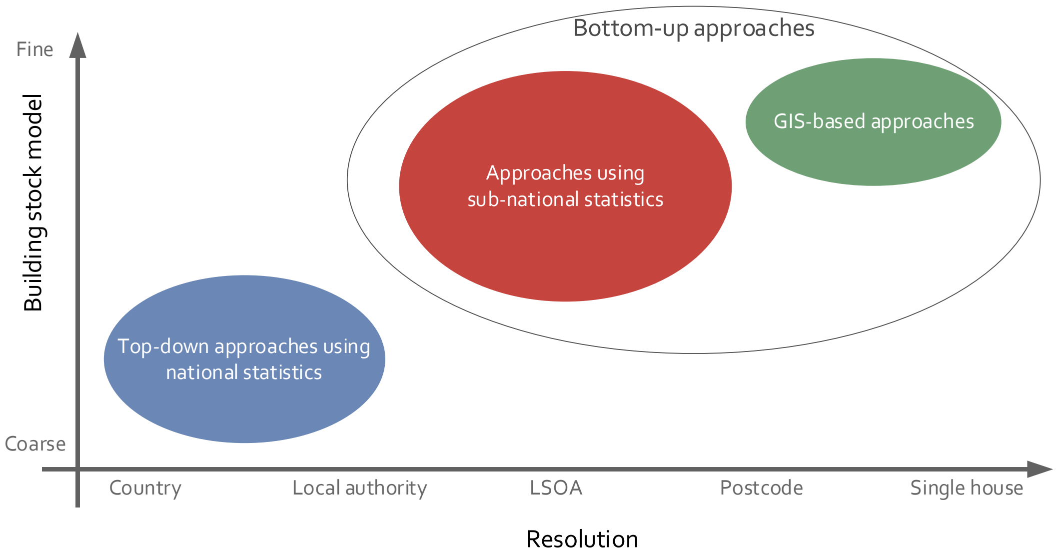


Figure 2-6: Methods to estimate heat demand at different resolutions and their capability to produce a detailed building stock model

2.4 Review of Methods to Synthesise Heat Demand Profiles to Study Heat Decarbonisation Pathways

In addition to estimating the annual heat demand to analyse the heat supply options, the heat demand profiles of heating technologies are used to assess the potential costs of the different heat decarbonisation pathways on the energy system. Hence, the capability of these profiles to correctly reflect the usage pattern and the peak demand of each heating technology is critical.

The magnitude and shape of the heat demand profile for a building can be characterised by considering the dwelling’s features (e.g., size of the building, type, etc.), its energy performance, occupancy schedule and also the type of heating technology. The two main approaches to produce these profiles that are identified in the literature are the building physics approach and the statistical approach using measured data (which is often referred to as the data-driven approach).

Delta-EE used a building physics model to study the electrification of heat in the Scottish power system [36]. Figure 2-7 shows the undiversified and diversified load profile of an air-to-water source heat pump (ASHP). The diversified profile accounts for several parameters, including occupancy schedule. A decrease of 20% of the peak load is observed when comparing the diversified load profile with the undiversified load. The minimum load during off-peak hours is close to zero in the two profiles. However, it is unlikely that in a group of thousands of ASHPs, no ASHPs would be running during these hours. Therefore, this profile is unrealistic because it underestimates the baseload. The timing and the size of the peak load are similar to other studies, as seen on p. 25 of the report [36].

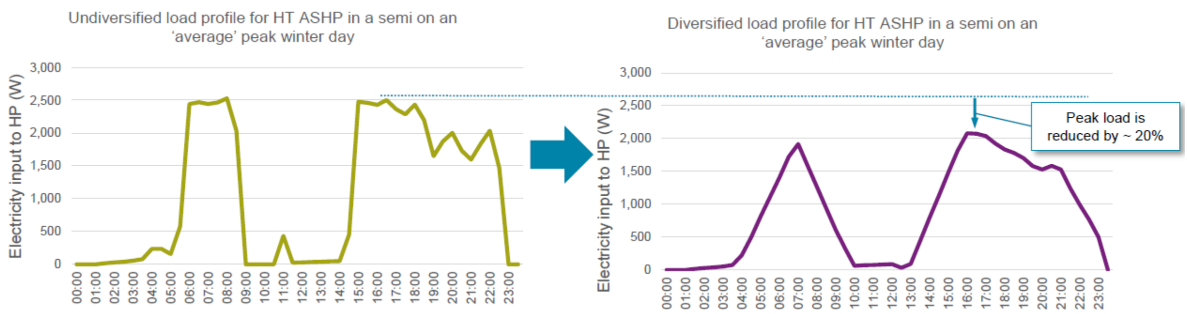


Figure 2-7: Undiversified and diversified high-temperature (HT) ASHP electricity load profiles in a semi-detached house for space heating and hot water from Delta-EE (source: figure from [36])

Another model, called CREST, is used to represent the thermal-electrical demand of the residential sector at high resolution (<1min) [37]. It combines several sub-models synthesising electrical demand, thermal demand and hot water demand, with an occupancy model mimicking the behaviour of users. This type of model is useful when no other data is available or for specific study requiring high resolution data, but it has limitations that would need to be considered when doing energy modelling. The limitations include the parameters to calibrate the models such as the characteristics dwellings to model, the behaviours of users, the amount of diversity to consider, etc. Figure 2-8 shows the gas demand of 104 dwellings for a winter day modelled using CREST compared to two sources of data: EDRP and Carbon Trust. The CREST gas demand data is peaking in the morning whereas the EDRP data, which is considered by the authors as representative of the UK average is peaking in the afternoon. There are also occurrences where the CREST gas demand data is 0 similarly to the previous model used by Delta-EE.

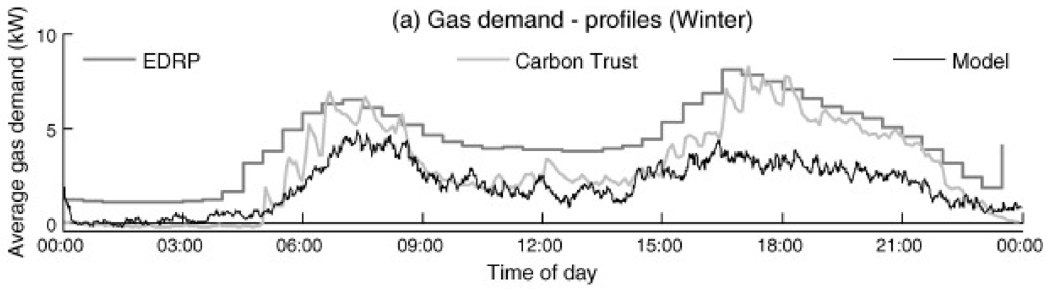


Figure 2-8: Gas demand profiles produced by the CREST model (model), the EDRP and the Carbon Trust (source: figure from [37])

Fisher et al. [38] use a combination of a building physical model and a behavioural model to produce space heating and domestic hot water demand profiles for dwellings in Germany. The results are compared with hourly measured data for a day and they show that the total daily energy demand is accurately captured but peaks are underestimated during some of the day. In particular, the synthesised peak in the late morning is 5 to 45% lower than the peak of the measured data.

The same method was used to produce heat demand profiles of HPs in some European countries[39]. The synthesised daily energy demand was validated using UK gas demand data but not the hourly profiles.

Overall, the physical model of a building provides an understanding of the annual heat demand but will often fail to synthesise realistic heat demand profiles. A statistical approach using measured data from real systems can be used to overcome this problem. The measured data embeds information about the occupancy schedule, occupants' behaviour regarding the control of their heating system and the diversity factor of the group of units, which can be extracted by a statistical model and used to synthesise heat demand profiles.

In [40], Sansom used micro-CHP units and gas boiler gas consumption data from a trial of 71 dwellings to derive half-hourly heat demand for the UK. The profiles of the micro-CHP units are used as an approximation of the profiles for electricity-based heating technologies to overcome the lack of available data at the time. A similar approach was used in [41] to study the impacts of the electrification of heat in the UK, except that measured data from a district heating scheme was used.

The results from Sansom [40] were enhanced by using the gas consumption data of gas boilers from a larger trial to refine the UK heat demand profile [30]. The new profile showed a decrease of 40% of the estimated half-hourly peak heat demand compared with the original profile.

The methods that are used to synthesise electricity demand profiles are also relevant because the same approach can be used for heat demand profiles. A review of the different methods of the statistical approach using measured data can be found in [42]. This study also describes some of the main methods, including artificial neural network, support vector machine, decision tree and statistics regression techniques.

Jenkins et al. [43] use a Hidden-Markov model to synthesise electricity demand profiles at minute resolution for a single dwelling and then compare the aggregated results. With the correct input data and assumptions, heat demand profiles can be synthesised.

From this review, it can be seen that building physics models are a good option to estimate the heat demand of dwellings at low resolution but will fall short when synthesising hourly or higher resolution profiles. Meanwhile, models built using measured data based on a statistical approach can provide better estimation if provided with sufficient data.

Measure data can also be used to extract information about the characteristics of heating systems, such as After Diversity Maximum Demand (ADMD), peak time and patterns. Wang et al. [44] use half-hourly gas and electricity from 18,370 dwellings to extract these characteristics to inform the sizing of district heating schemes. The same information can be used to estimate the peak heat demand produced by a group of dwellings using gas boilers. Similarly, Love et al. [45] use 2min resolution electricity consumption data from a heat pump trial to estimate the additional half-hourly peak electricity demand created by uptake of HPs in GB. They find that the ADMD of HPs is around 1.7 kWe, and that the GB peak will increase by 14% with an uptake of 20% .

2.5 Models to Study the Decarbonisation of Heat

The challenge of decarbonising heat has led to a growing number of research studies in the heating sector. Several approaches have been developed and the heat supply options have been shown to be impacted by modelling assumptions, including spatial resolution and details of the building stock.

The impact of spatial resolution on the outcomes of a model to optimise heat supply options in urban areas was demonstrated in [31]. The uptake of district heating networks in the UK was assessed using data at three levels of spatial resolution, as follows: LSOAs, MSOAs and local authorities. The results of this model showed a 20%

increase in the number of dwellings connected to district heating networks when using LSOA compared to MSOA as the spatial resolution. Using LSOA instead of local authority area as the spatial resolution resulted in a 30% increase in the number of dwellings connected to heat networks.

Dodds et al. showed in[46] that the use of a more detailed building stock model would have a direct impact on the heat supply options. The outcomes from two versions of the MARKAL model were compared: the base version and a revised version that included a simplified housing stock model. The disaggregated results from the revised version show the impact of the house type on the selected heat technologies, while providing similar aggregated heat demand with the base version of the model.

A limited number of studies have investigated heat decarbonisation in local areas considering fine spatial resolution with a detailed representation of the building stock. Scamman et al. in [47] reviewed the models that have recently been used to assess the UK heat decarbonisation strategy and only the model used in [31] was found to be suitable. Outside the UK, additional models were found to optimise heat supply options by individual buildings, sectors or areas.

The heat supply options for 69 buildings near Porto, Portugal were assessed [48]. For each building, the heat demand and the temporal profiles were estimated and simulated in five scenarios. The results suggested that district heating using waste heat and individual HPs with photovoltaic panels were the best cost-competitive options.

The authors of [49] investigated scenarios including different levels of expansion of the existing district heating network, individual heating systems and heat savings for Helsingør in Denmark. They divided the local authority into smaller areas based on the heat density and the proximity to the existing district heating. By simulating eight scenarios and using a least-cost approach, they suggested that an expansion of 39% of the district heating and 39% heat savings could be reached.

Additional studies focusing solely on district heating used similar approaches. Several heat decarbonisation scenarios for an existing district heating project in a German city were analysed by [50]. An energy dispatch model with the heat demand represented by a single node was used and the results suggest that large-scale HPs integrated into district heating can help with heat decarbonisation but their viability depends on electricity and CO2 prices. Using a heat demand atlas, the authors in [35] built a custom model to assess the areas viable for district heating by aggregating the results from each 100x100m cells [51]. The results show that in the countries considered, 59% of the 2015 heat demand is economically viable to be supplied by district heating.

2.6 Summary of the Challenges

This review of the heat decarbonisation pathways for the UK and Wales showed that the heat-supply mixes have a very different share of individual HPs, individual hydrogen boilers, individual hybrid systems and district heating. It also shows the uncertainties and the lack of consensus regarding how to decarbonise heat. This is reflected at a local level in Wales, where no local authority has a detailed plan to decarbonise the residential heat sector.

In terms of technical challenges, a review of the methods and models used in heat decarbonisation studies has shown that:

- There are heat decarbonisation pathways available at the national level but there is no information about how these pathways would be translated to local areas, except the work done on the electrification of heat by DNOs. This lack of methodology makes it difficult for local areas to develop their own heat decarbonisation pathways and investigate their impacts on the local energy infrastructure.
- Residential heat demand data availability at high resolution is scarce. Several methods to estimate heat demand in local areas exist but there is a need for a method that does not rely purely on gas data, and which provides heat demand data at high resolution as well as information regarding the building stock. This type of data is crucial to create a baseline of the current system and develop heat decarbonisation pathways based on the specificities of the area.
- Heat demand profiles for different heat technologies are not currently available. These are essential to estimate the peak energy demand and the timing of the demand of heat decarbonisation pathways, and to quantify their impacts on the energy infrastructures. Currently, the use of a single heating technology profile to approximate the profiles of other technologies leads to significant errors in the estimation of the impacts of the uptake of some heating technologies such as heat pumps.
- The models to assess the viability of heat supply options either focus on a single heating technology, do not use a detailed building stock model, or are not flexible enough to use high-resolution heat demand data. This makes it difficult to develop heat decarbonisation pathways for local areas without having a bias toward specific heating technologies.

3 Annual Heat Demand for Dwellings

3.1 INTRODUCTION

The literature review showed that analysis of local heat supply options requires an estimate of the heat demand from the dwelling stock. However, this can be difficult because of the limited amount of measured heat demand data available at fine resolution and also because of the lack of consistent building stock information across different areas.

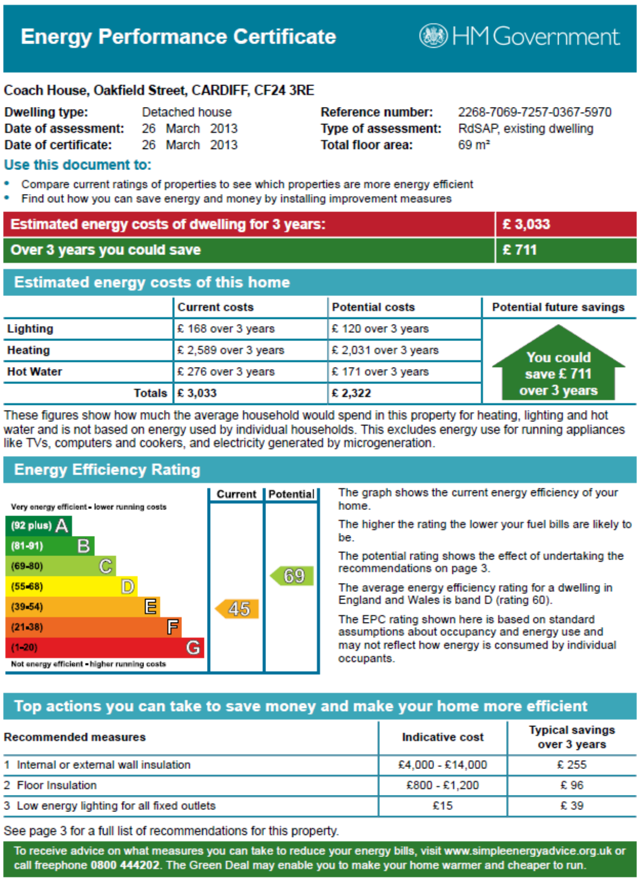
In this chapter, I will describe a method to estimate the annual heat demand for dwellings at fine spatial resolution for different categories of dwellings, before and after implementing potential energy efficiency measures. This method will then be demonstrated in case studies of the local authorities of Cardiff, Swansea and Newport.

3.2 METHODOLOGY

Building stock data and energy performance information of dwellings were used to estimate the annual heat demand of dwellings in the local area. The annual heat demand of the existing building stock with and without energy efficiency improvements was then calculated.

The total annual heat demand for a local area was derived by multiplying the average annual heat demand of each dwelling category by the number of dwellings in the area in that dwelling category and then aggregating the results. In this project, 16 dwelling categories were used, with a *dwelling category* being the combination of a dwelling type (i.e., detached, semi-detached, terraced and flat) and a heating system (i.e., natural gas boiler, resistance heater, biomass boiler and oil boiler).

Energy Performance Certificates (EPC) were used to estimate the annual heat demand of different dwelling categories within a local area for a typical year. Figure 3-1 shows an EPC for a detached house with a current energy efficiency rating of 45 (band E) and a potential energy efficiency rating of 69 (band C) - on a scale from 0 (band G) the worst, to 100 (band A) the best. The space heating and hot water demand considering current and potential energy efficiency ratings are also estimated in the EPC.



Energy Performance Certificate HM Government

Coach House, Oakfield Street, CARDIFF, CF24 3RE

Dwelling type:	Detached house	**Reference number:**	2268-7069-7257-0367-5970
Date of assessment:	26 March 2013	**Type of assessment:**	RdSAP, existing dwelling
Date of certificate:	26 March 2013	**Total floor area:**	69 m²

Use this document to:

- Compare current ratings of properties to see which properties are more energy efficient
- Find out how you can save energy and money by installing improvement measures

Estimated energy costs of dwelling for 3 years:	**£ 3,033**
Over 3 years you could save	**£ 711**

Estimated energy costs of this home

	Current costs	Potential costs	Potential future savings
Lighting	£ 168 over 3 years	£ 120 over 3 years	You could save £ 711 over 3 years
Heating	£ 2,589 over 3 years	£ 2,031 over 3 years	
Hot Water	£ 276 over 3 years	£ 171 over 3 years	
Totals	£ 3,033	£ 2,322	

These figures show how much the average household would spend in this property for heating, lighting and hot water and is not based on energy used by individual households. This excludes energy use for running appliances like TVs, computers and cookers, and electricity generated by microgeneration.

Energy Efficiency Rating

The graph shows the current energy efficiency of your home.

The higher the rating the lower your fuel bills are likely to be.

The potential rating shows the effect of undertaking the recommendations on page 3.

The average energy efficiency rating for a dwelling in England and Wales is band D (rating 60).

The EPC rating shown here is based on standard assumptions about occupancy and energy use and may not reflect how energy is consumed by individual occupants.

Top actions you can take to save money and make your home more efficient

Recommended measures	Indicative cost	Typical savings over 3 years
1 Internal or external wall insulation	£4,000 - £14,000	£ 255
2 Floor Insulation	£800 - £1,200	£ 96
3 Low energy lighting for all fixed outlets	£15	£ 39

See page 3 for a full list of recommendations for this property.

To receive advice on what measures you can take to reduce your energy bills, visit www.simpleenergyadvice.org.uk or call freephone **0800 444202**. The Green Deal may enable you to make your home warmer and cheaper to run.

Figure 3-1: Example of an EPC for a detached house[52]

The EPC database for all local authorities (with spatial resolution at postcode level) in England and Wales was downloaded from the open data communities platform [52]. The data were cleaned, and outliers were removed. The cleaning process entailed:

1. Removing the EPCs where the potential heating cost is more than 10% higher than the current heating cost. For a dwelling, the energy efficiency measures recommended on an EPC can decrease the heat gains from appliances (i.e., switching to LED lights) increasing the heat demand to be supplied by the heating system and thus the heating cost.
2. Using 15 kWh/m2 as the minimum threshold for the heat consumption of a dwelling, which is equivalent to a passivHus requirement.
3. Using 400 kWh/m2 as the maximum threshold for the heat consumption in a dwelling.
4. Removing the dwellings with an unspecified number of rooms.
5. Grouping the EPCs into dwelling categories. The dwellings' postcodes were also used to link them to an LSOA, MSOA and LA using a lookup table published by the ONS [53].

Figure 3-2 illustrates the methodology that was used to calculate the residential annual heat demand of each dwelling category of an LSOA using the cleaned EPC database, which includes the following steps:

1. The average heat demand was calculated for each dwelling category from the cost for heat demand displayed on the EPCs which was converted using 2016 SAP fuel prices4 and the efficiencies of heating systems shown in the Appendix F.4,
2. Given that not all the dwellings in a LSOA have an EPC (an EPC is not mandatory and is mostly performed when a dwelling is sold or rented), when the number of EPCs for a dwelling category was too low to estimate the average heat demand, the average heat demand for this dwelling category was calculated by running steps 1 to 3 for an extended geographical area (i.e., MSOA, LA, and Country).
3. The annual heat demand of each dwelling category was calculated.
4. The residential heat demand of the LSOA was calculated by aggregating the annual heat demand for all the dwelling categories in the LSOA.

In this paper, this is described as the *EPC-based* method.

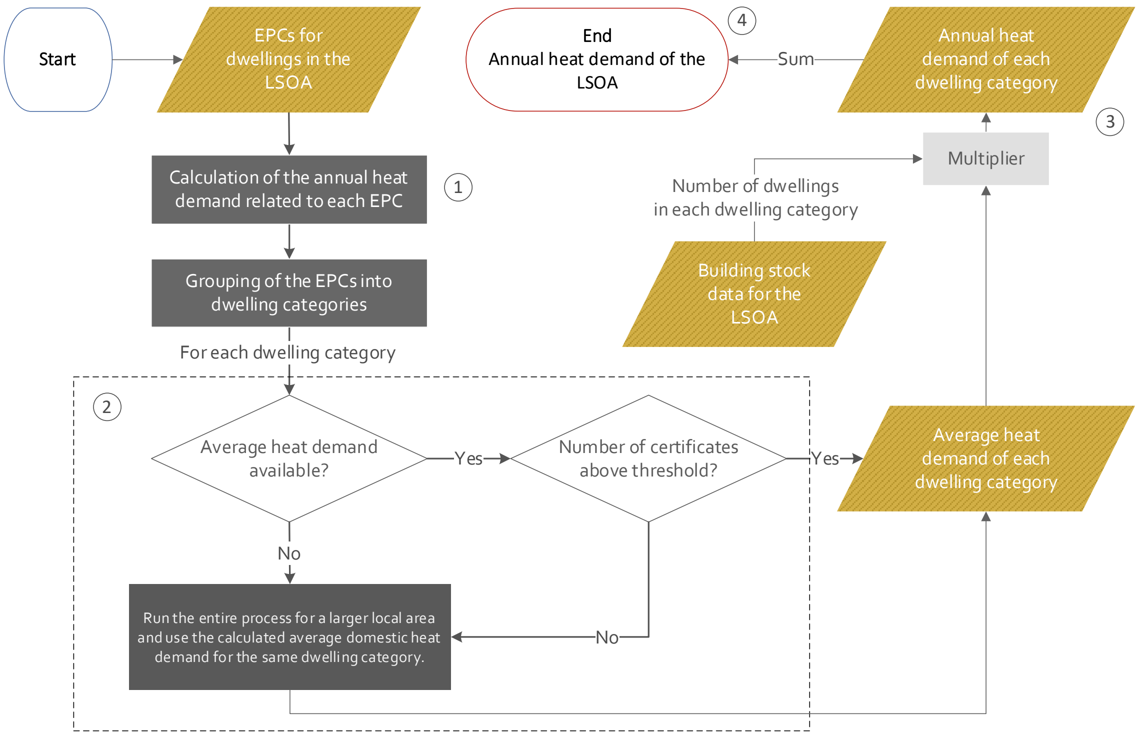


Figure 3-2: The process used to estimate the heat demand of an LSOA.

[4] Fuel prices used are available at this address: https://www.bre.co.uk/filelibrary/SAP/2012/RdSAP-fuel-prices-from-January-2018.xlsx

3.3 Annual Heat Demand of Dwellings in Cardiff, Swansea and Newport

The EPC-based method was used to calculate the annual heat demand before and after energy efficiency measures for the LSOAs of Cardiff, Swansea and Newport. For each LSOA, the number of dwellings, their types and their heating systems were extracted from the census data for 2011 [1]. This data was available for 2011 and was projected to 2018 based on the change in the number of dwellings published by [54]. The share of dwellings in each dwelling category was kept the same between 2011 and 2018..

Figure 3-3 shows the number of heating installations by dwelling type in Cardiff, Swansea and Newport in 2018. The gas boiler is the dominant heating technology. Semi-detached and terraced dwellings are the main dwelling types. In total, there were 153,106 dwellings in Cardiff, 108,790 in Swansea and 65,117 in Newport in 2018.

The combination of dwelling types and heating technologies defined 16 dwelling categories for which annual heat demand was estimated.

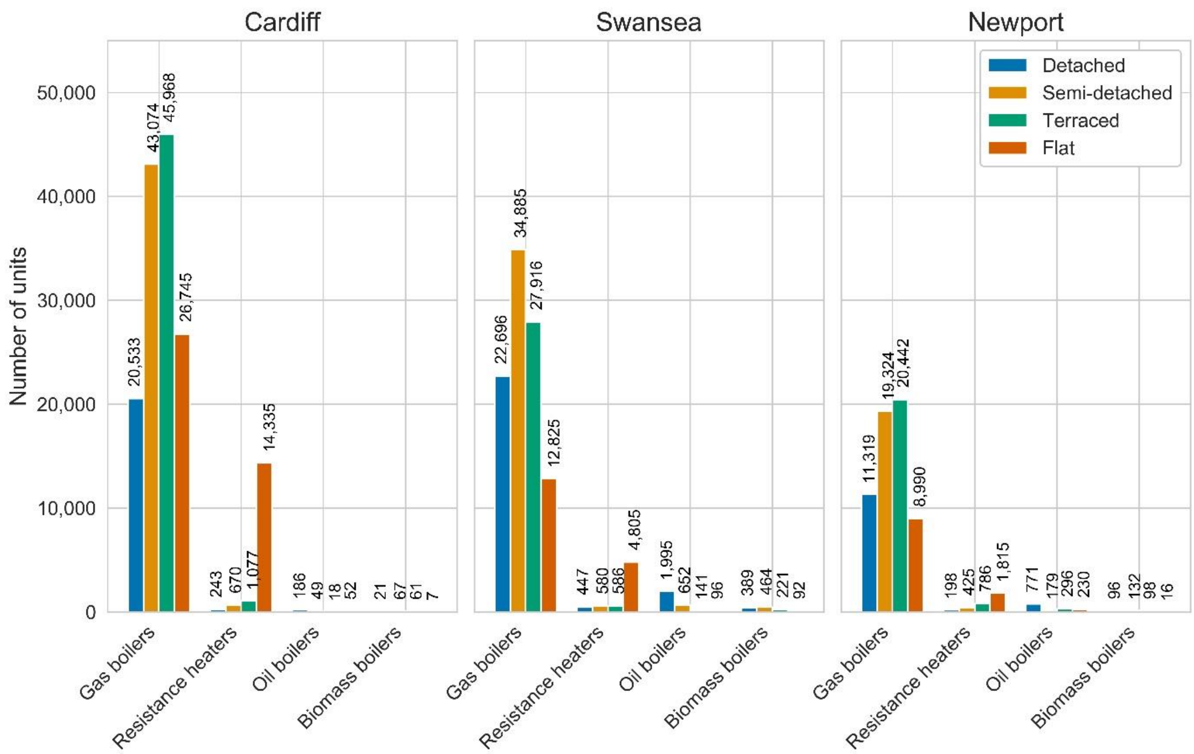


Figure 3-3: Heating technology by dwelling type in Cardiff, Swansea and Newport in 2018

Figure 3-4 shows the number of EPCs that are used as an input to the EPC-based method to calculate the average annual heat demand of each dwelling category for the three local authorities. Note that the small number of EPCs for dwelling categories such as “detached biomass boiler” increases the potential for extreme values. For instance, in a local authority where the average annual heat demand for detached dwellings with biomass boilers is 15,000 kWh, there is a LSOA where there are four of these dwellings. Three of them have a heat demand of 15,000 kWh and one has a demand of 80,000 kWh, the average heat demand of this dwelling category in this LSOA will be 31,250 kWh. It is more than twice higher than the average of the annual heat demand of this building category in the local authority. With higher number of dwellings of the same dwelling category in each LSOA, this type of differences would be minimised and the average heat demand in each LSOA will be closer to the average heat demand of the local authority.

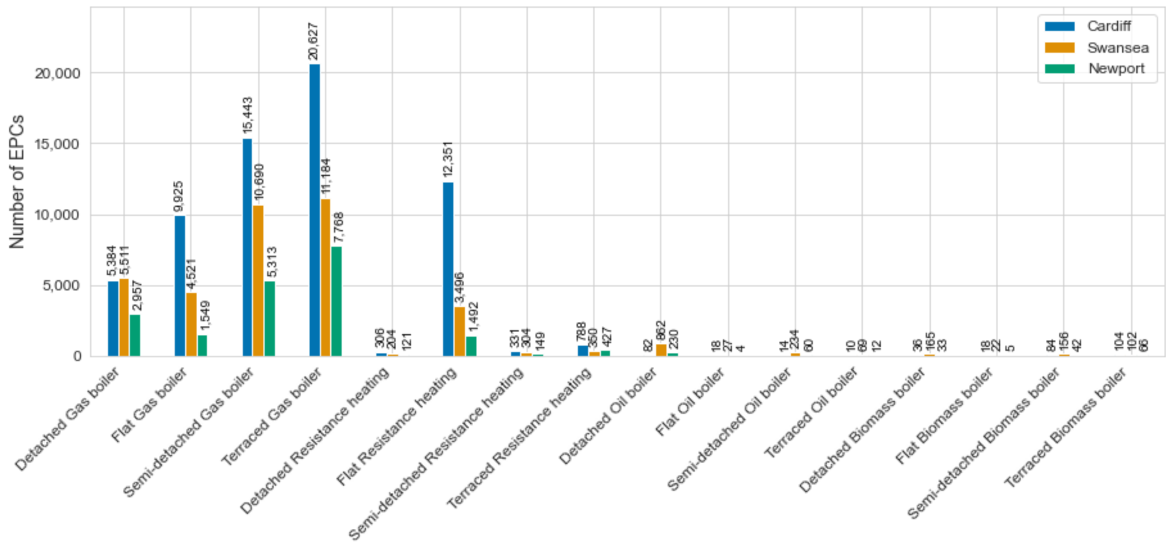


Figure 3-4: Number of EPC entries used to calculate the annual heat demand of each dwelling category in Cardiff, Swansea and Newport.

There were individual dwellings with multiple EPCs associated to them. The same dwelling could have had multiple EPCs done over the years. These duplicates were not removed from the input data to the EPC-based method because they were not expected to have major impacts on the results. Table 3-1 shows the difference in the number of EPCs when considering duplicates. It would decrease the size of the input data by between 41 to 33% across the three local authorities compared to the total number of EPCs.

It is not clear what may be the impacts of removing these duplicates on the estimated annual heat demand before considering energy efficiency measures. For a dwelling, the most recent the EPC may show that the EPC with the lowest heat consumption due to energy efficiency measures being implemented. However, it may be also possible that the dwellings have deteriorated with time which made their heat consumption increase. Further analysis would need to be conducted to estimate what would happen to the estimated annual heat demand by removing duplicates. No large difference is expected for the estimated annual heat after considering energy efficiency measures.

Table 3-1: Comparison of the number of EPCs with and without duplicates in Cardiff, Swansea and Newport.

	Cardiff	Swansea	Newport
Number of EPC entries (with duplicates)	65,648	38,060	20,273
Number of EPC entries (without duplicates)	38,647	25,373	13,527

3.3.1 Annual Heat Demand Before Energy Efficiency Improvements

Figure 3-5 shows the estimated average annual heat demand before energy efficiency improvements of the 16 dwelling categories in Cardiff, Swansea and Newport. Detached houses have the highest annual heat demand on average, followed by semi-detached houses, terraced houses and flats. Within dwelling categories with the same dwelling type (e.g., detached), the annual heat demand varies depending on the heating system used. This can be explained by the underlying attributes, such as the age of the dwelling, the gross internal area, and the energy efficiency level. For instance, detached houses with resistance heaters are on average smaller in size and more energy-efficient than detached houses with oil boilers according to the EPC data.

The variation in the average annual heat demand by location for the same dwelling category may be explained by the small numbers of EPC for these dwelling categories in some LSOAs and across the entire local authority (see Figure 3-4). The largest variations are seen for detached and semi-detached houses where the annual heat demand can be up to 8 times higher than the average.

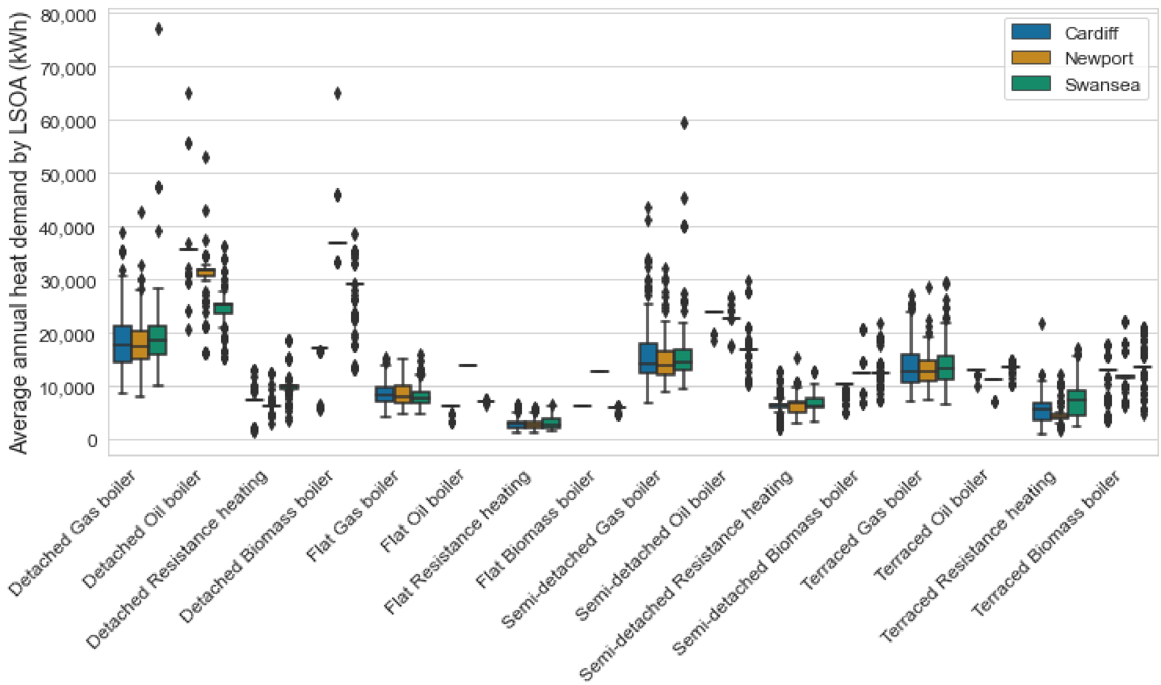


Figure 3-5: Boxplot of the annual heat demand before energy efficiency improvements of the 16 dwelling categories by LSOA in Cardiff, Swansea and Newport.

Figure 3-6 to Figure 3-8 show the maps of the annual heat demand of dwellings by LSOA calculated using the EPC-based method for Cardiff, Swansea and Newport in 2018. This method combined the number of dwellings in each dwelling category (Figure 3-3) with the average annual heat demand before energy efficiency improvements of the 16 dwelling categories (Figure 3-5).

The annual heat demand of dwellings for the three cities in 2018 was estimated at **Cardiff: 1,981 GWh**, **Swansea: 1,562 GWh** and **Newport: 906 GWh**. This represents an average annual heat demand of 12,900 kWh per dwelling in Cardiff, 14,400 kWh in Swansea and 13,900 kWh in Newport. Despite these similarities, the heat demand density, based on the geographical area of the LSOAs, varies from close to 0 kWh/m^2 in some LSOAs to more than 120 kWh/m^2 in others. These characteristics will impact the suitability of heat supply options, such as district heating networks.

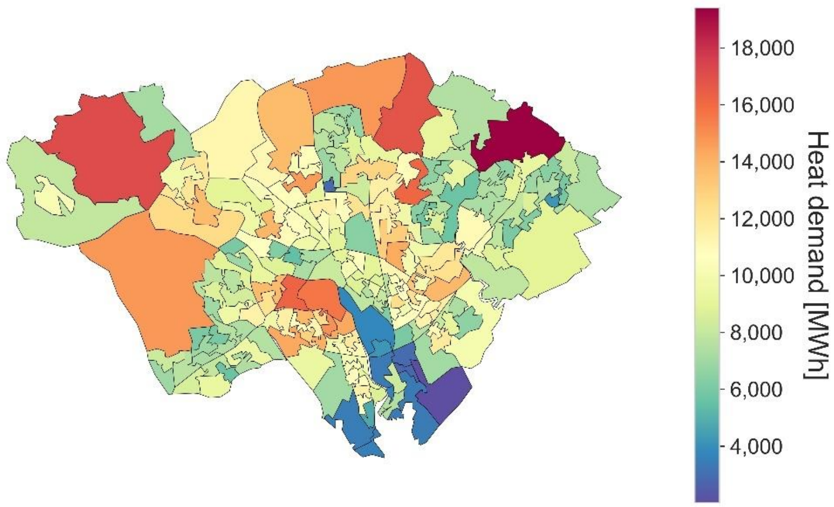


Figure 3-6: Intensity map of the estimated residential annual heat demand in MWh before energy efficiency improvements by LSOA in 2018 for Cardiff.

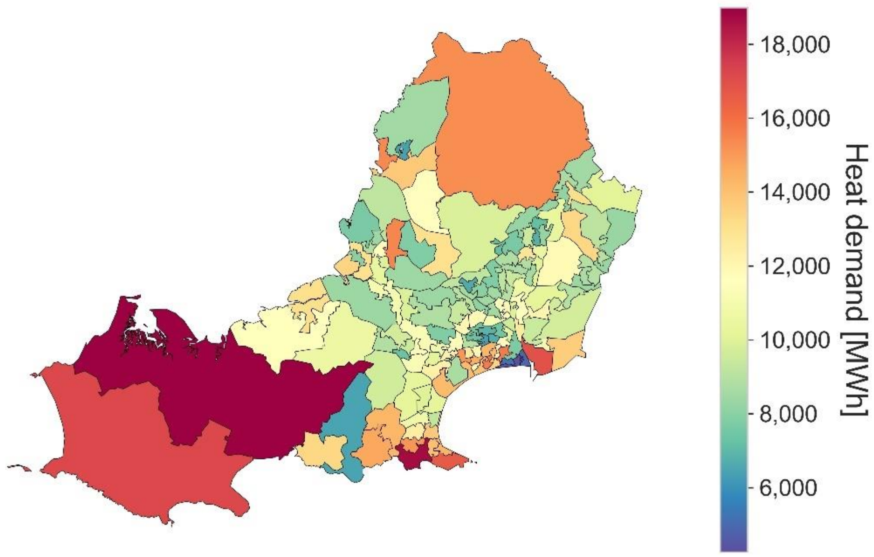


Figure 3-7: Intensity map of the estimated residential heat demand in MWh before energy efficiency improvements by LSOA in 2018 for Swansea.

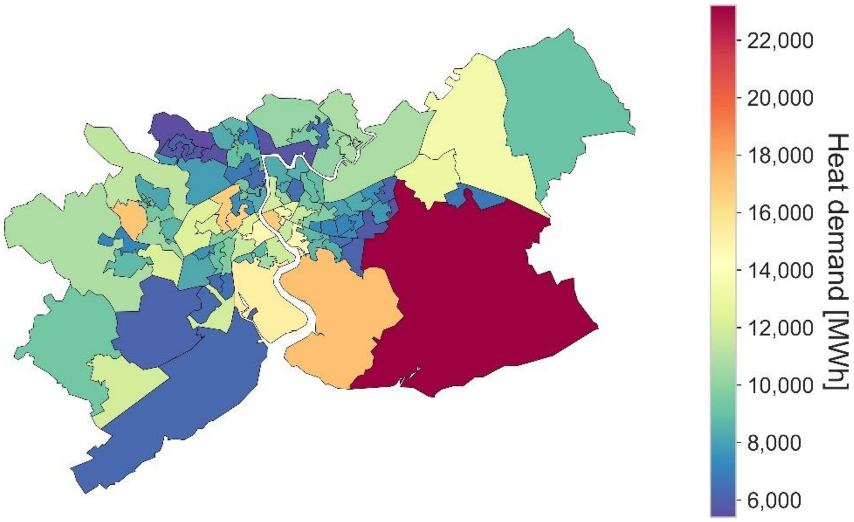


Figure 3-8: Intensity map of the estimated residential heat demand in MWh before energy efficiency improvements by LSOA in 2018 for Newport.

3.3.2 Impact of Energy Efficiency Improvements on Heat Demand

The potential of the energy efficiency measures depends on the building stock and differs by LSOA. By counting the number of EPCs in each band (e.g., A,B,C,D,E,F and G) that improved their energy efficiency rating when considering energy efficiency improvements and by how much, the share of dwellings that can improve their current EPC rating was identified. Furthermore, using the potential space heating and hot water demand displayed in EPCs, the potential heat demand after energy efficiency measures was calculated and compared with the current values for each dwelling category using the EPC-based method described in 3.2 This was calculated using the cleaned EPC dataset that was used to estimate the current annual heat demand of each dwelling category.

Figure 3-9 to Figure 3-11 show how the current EPC ratings of buildings in Cardiff, Swansea and Newport could be improved. Overall, 84% of buildings with an EPC in Cardiff have the potential to reach an energy efficiency rating equal to or above C. This ratio reaches 85% for Newport and 83% for Swansea.

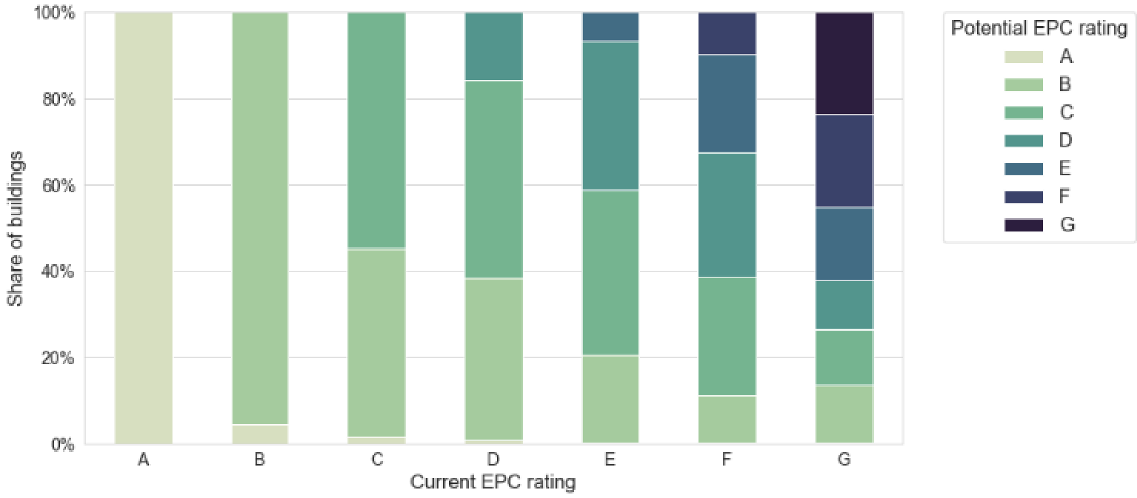


Figure 3-9: Potential improvement in the energy efficiency of dwellings with a valid EPC in Cardiff. Current ratings mean ratings before energy efficiency improvements and potential rating mean ratings after energy efficiency improvements.

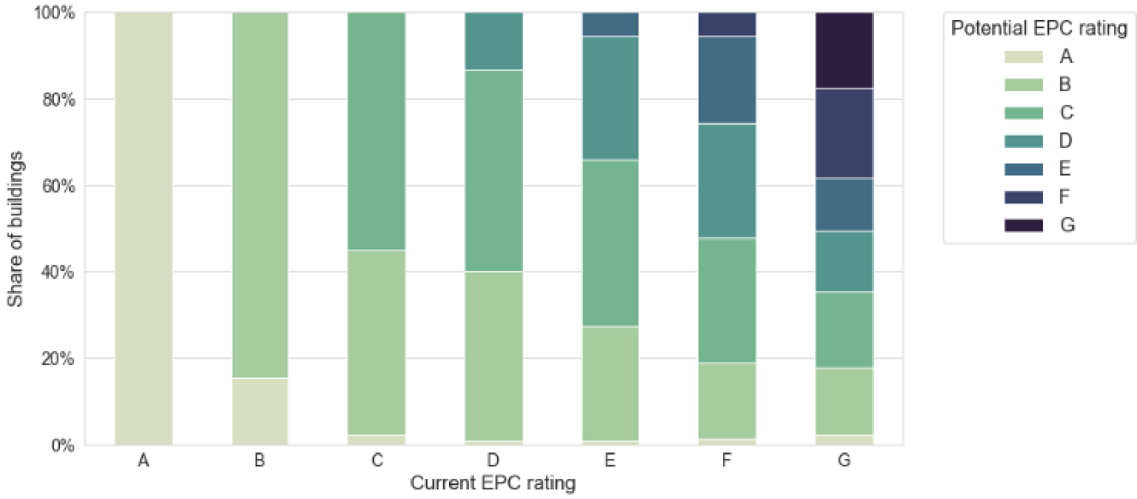


Figure 3-10: Potential improvement in the energy efficiency of dwellings with a valid EPC in Swansea. Current ratings mean ratings before energy efficiency improvements and potential rating mean ratings after energy efficiency improvements.

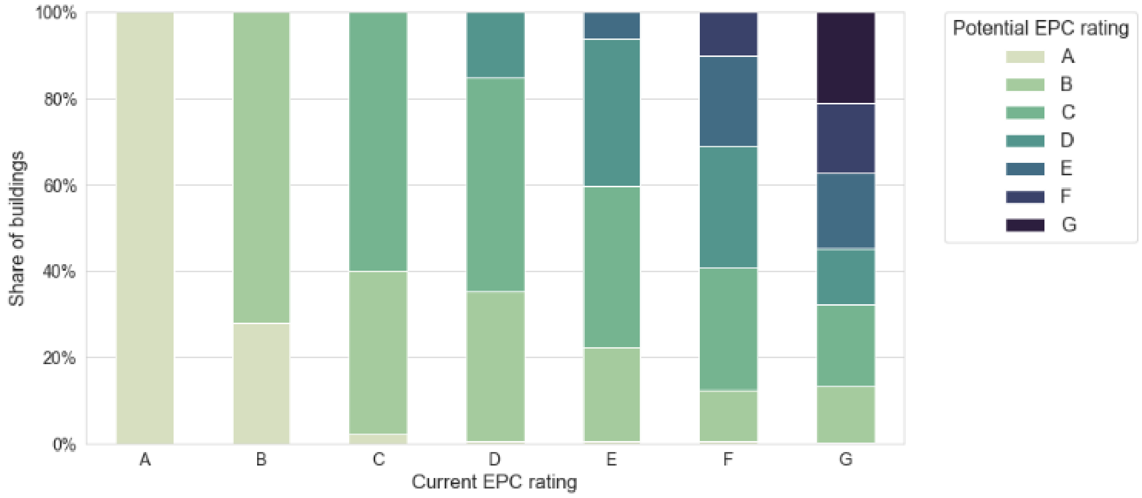


Figure 3-11: Potential improvement in the energy efficiency of dwellings with a valid EPC in Newport. Current ratings mean ratings before energy efficiency improvements and potential rating mean ratings after energy efficiency improvements.

Figure 3-12 compares the average annual heat demand of each dwelling category in Cardiff, Swansea and Newport before and after energy efficiency improvements. Based on the 2018 building stock data for these local authorities, if all of the recommended energy efficiency measures in EPCs were to be implemented, then the annual heat demand would decrease by on average 30% in Cardiff and Newport, and 32% in Swansea.

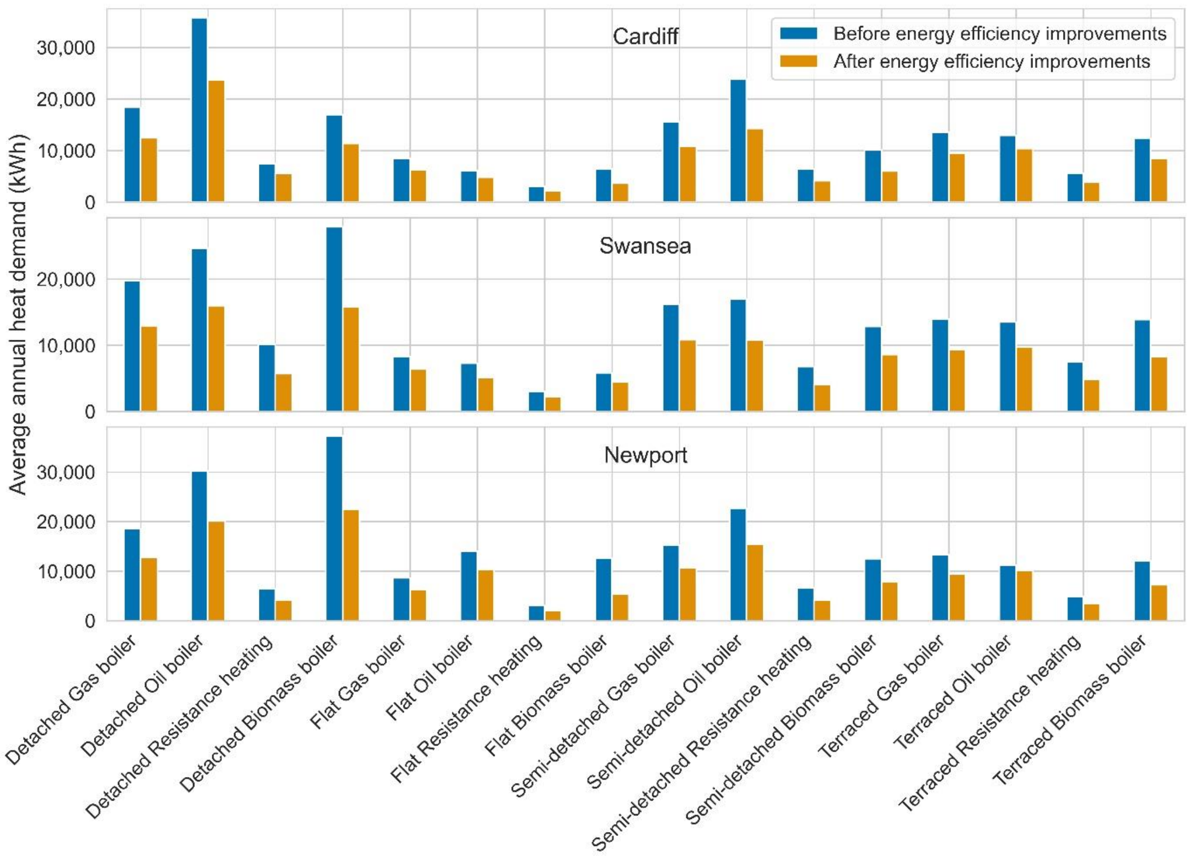


Figure 3-12: Average annual heat demand by dwelling category based on current and potential energy costs in Cardiff, Swansea and Newport.

3.3.3 Validation of the Results of the EPC-based Method

The estimated annual heat demand before energy efficiency improvements (shown in Figure 3-5) were compared to two external sources for validation. The first source was used to compare the annual heat demand of dwellings by heating fuel and the second source compared the heat demand from gas at LSOA level.

3.3.3.1 Comparison with the Average Residential Heat Demand by Fuels from the Study by the Centre for Sustainable Energy (CSE)

The Centre for Sustainable Energy (CSE) studied the energy usage of different dwellings in Great Britain, based on 32,700 housing surveys. The outputs of this study included average annual heat demand by heating fuels: gas, electricity and non-metered fuels (e.g., oil and biomass) [55]. Figure 3-13 shows a comparison of the heat demand from the CSE study with the estimated heat demand by heating fuels produced by the EPC-based method (Figure 3-5).

A comparison of the average annual heat demand shows that the values are in the same range. The largest discrepancy was observed for the non-metered heated dwellings, where the annual heat demand from the CSE study is 22% lower than the output of the

EPC-based method applied to non-metered dwellings in Cardiff, Swansea and Newport. Two main reasons might explain this difference: the accuracy of the heat demand estimated in the EPC of non-metered buildings, and the assumptions for the efficiency rating of the heating technologies.

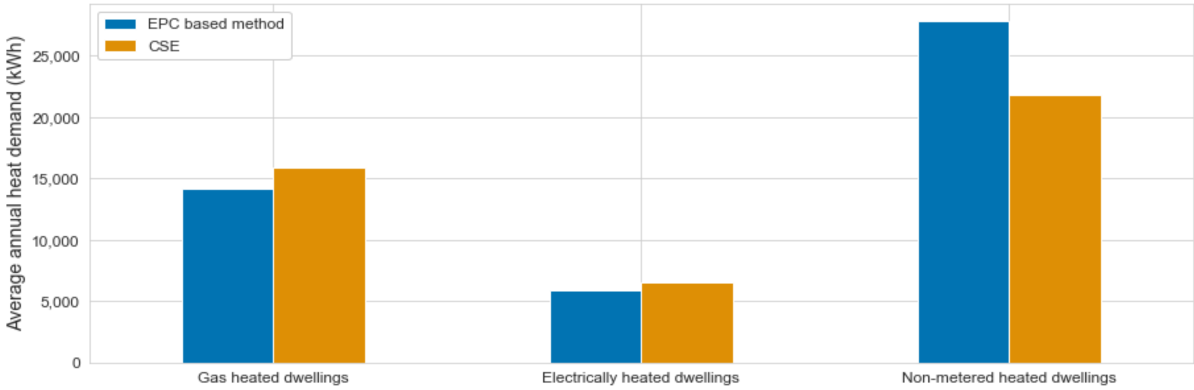


Figure 3-13: Comparison of the average annual heat demand of dwellings heated with gas, electricity and non-metered fuels from the CSE report [55] and the EPC-based method aggregated for Cardiff, Swansea and Newport

3.3.3.2 Comparison with Gas Demand Data

Data on gas consumption in the residential sector at the LSOA level in England and Wales is published on the BEIS website [32]. This gas consumption data is calculated from gas supply points data received from gas shippers. The gas consumption data is weather corrected and matched with geographical areas. This gas consumption data was then used to estimate heat demand for each LSOA and the result was compared with heat demand produced by the EPC-based method. All of the heat demand data presented in this section is weather corrected.

The energy consumption statistics published by BEIS [56] show that 97.5% of the residential gas consumption is used for space heating and hot water. A report from Delta-EE [57] suggested that gas boilers have an average efficiency of 84%. Hence, for each LSOA, gas consumption data was used to estimate annual heat demand through:

$$Heat\ from\ gas_{LSOA} = BEIS\ gas\ consumption_{LSOA} \times 97.5\% \times 84\% \qquad (1)$$

Figure 3-14 to Figure 3-16 show the heat demand in dwellings supplied by gas in 2018, which is derived from the EPC-based method and gas consumption data from BEIS. The values of the EPC-based method are consistently greater than the results produced from the BEIS data, but the two sets of data follow the same pattern. These differences might be explained by the decrease in the residential gas consumption that has happened almost continuously since 2010 due to a combination of factors, including efficiency measures, recession, increase in prices, and changes in building stock and household composition as shown in the data from BEIS [3]. This decrease might not be fully reflected in the procedure used to create EPCs, and thus in the EPC-based method. In addition, BEIS pointed out that there was missing or unallocated data, which could result in an underestimation of the gas consumption in LSOAs [58].

Another explanation is that the BEIS data may be weather corrected in a different way than the EPC-based method data. In a methodology document, the BEIS gas consumption data was mentioned to be "weather desensitised" using adjustment factors provided by the gas industry [59]. Further investigations are required to establish if those factors are impacting the differences seen in the results.

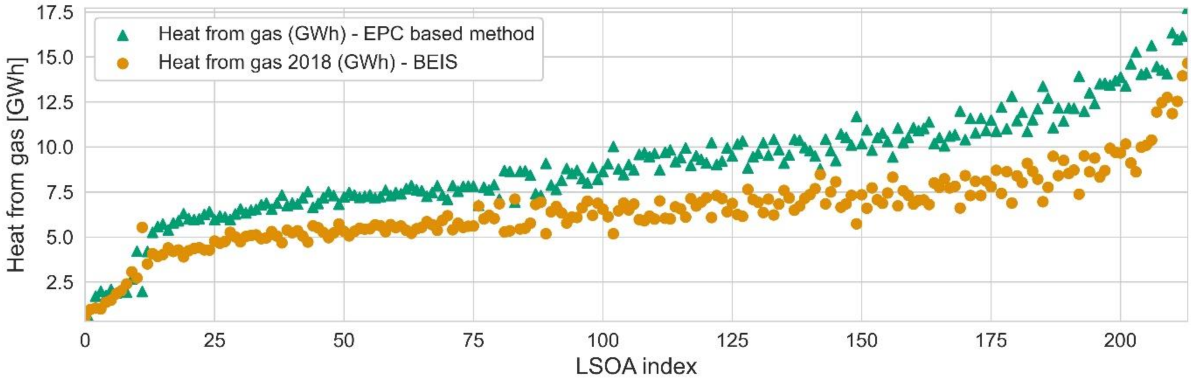


Figure 3-14: Scatter plot showing the heat supplied from gas for the same LSOAs level in Cardiff using data published by BEIS for 2018 (Δ) and using the EPC-based method (o).

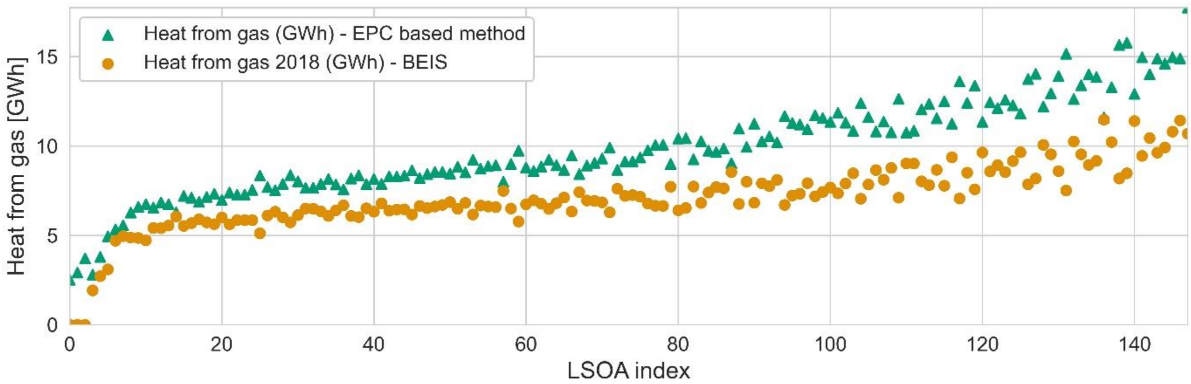


Figure 3-15: Scatter plot showing the heat supplied from gas for the same LSOAs level in Swansea using data published by BEIS for 2018 (Δ) and using the EPC-based method (o).

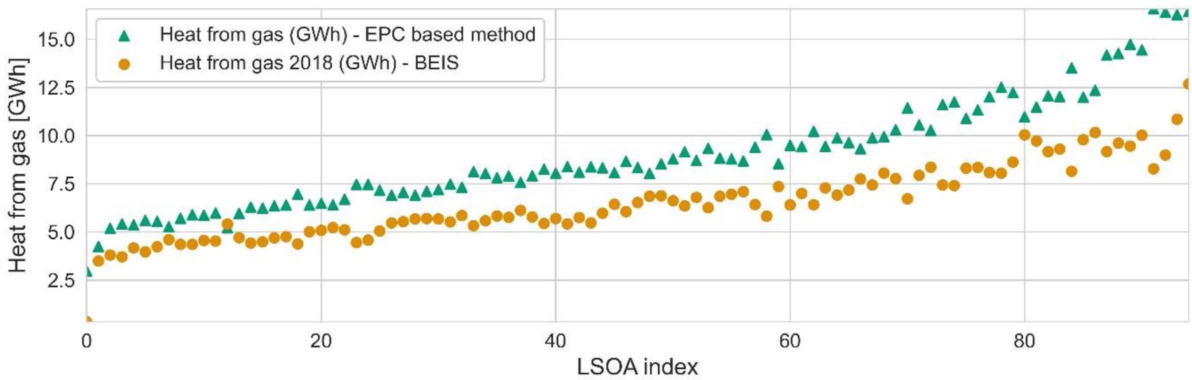


Figure 3-16: Scatter plot showing the heat supplied from gas for the same LSOAs level in Newport using data published by BEIS for 2018 (Δ) and using the EPC-based method (o).

Figure 3-17 shows the difference between the heat demand from gas using BEIS data compared to the EPC-based method in Cardiff, Swansea and Newport. The average difference is -24% for Cardiff, and -27% for Swansea and Newport.

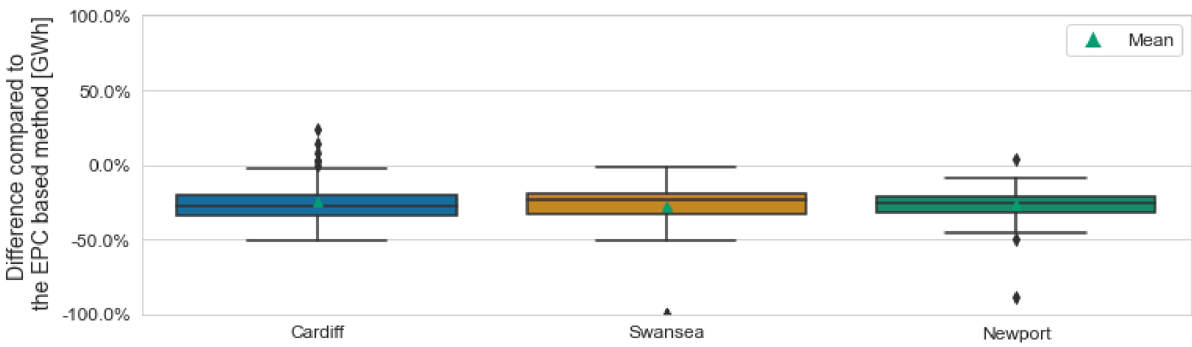


Figure 3-17: Box plot showing the difference between heat demand derived from gas consumption data from BEIS for 2018 compared to the heat from gas calculated using the EPC-based method.

These comparisons showed that the EPC-based method has potential and follow similar patterns than publicly available data. However, there are known limitations to EPCs because of the methods used to produce them, the quality of the recording [60] and the potential impacts of the use of duplicated EPCs in the input data.

EPCs assume a standard occupancy of the dwellings and thus do not consider potential differences in the behaviour of people and other socio-economic factors. These factors can have direct impact on the amount of heat demand.

Removing the duplicates from the input data would be expected to decrease the current annual heat demand before energy efficiency measures estimated in this study but no significant changes of the potential annual heat demand after energy efficiency measures are expected. Hence, this could lead to an overestimation of the amount of heat demand savings shown in this study.

3.4 SUMMARY

A method was proposed to estimate annual heat demand before and after energy efficiency improvements using a bottom-up approach. This method was demonstrated on case studies of the local authorities of Cardiff, Swansea and Newport but can be applied in any other local areas in which relevant data are available.

For these local authorities, Table 3-2 summarises the results. It shows that the average heat demand of dwelling categories before energy efficiency improvements vary from 3,000 kWh to more than 35,000 kWh, due to differences in dwelling types and heating technology. These values were validated against external sources, which gave confidence in the results.

Table 3-2: Average annual heat demand by dwelling category estimated using the EPC-based method and valid EPCs from Cardiff, Swansea and Newport

Average annual heat demand [kWh]		Heating systems			
		Gas boiler	Resistance heater	Oil boiler	Biomass boiler
Dwelling types	Detached	18,850	8,093	30,990	24,712
	Semi-detached	15,720	6,569	21,394	11,486
	Terraced	13,620	6,069	12,761	12,810
	Flat	8,447	3,041	8,110	7,527

The different number of dwellings and share of each dwelling category in LSOAs showed that their heat demand density, based on the geographical area of the LSOAs, ranges from 0 kWh/m^2 to more than 120 kWh/m^2, and their total heat demand ranges from 2,000 MWh to more than 20,000 MWh.

Energy efficiency measures for dwellings were estimated to have the potential to save 30% of the current heat demand. This is the equivalent of bringing more than 80% of the dwelling stock to an EPC rating of C.

With a more detailed knowledge of the dwelling stock and its characteristics at the LSOA level, it is possible to assess the impacts of different heat supply options on the energy system. However, to assess the impacts on the networks, more granular consumption data is required because annual data do not provide sufficient information, such as the peak energy demand or the daily energy consumption.

4 Half-hourly Heat Production and Energy Demand for Heating Technologies

4.1 INTRODUCTION

The magnitude and shape of the heat demand profile for a dwelling depends on the dwelling's form, its size, its energy efficiency, the occupancy schedule and the type of heating technology. While the EPC of a building can provide an understanding of its annual heat demand (Chapter 3), using measured data from heating systems to train a model is an effective approach to synthesise half-hourly heat production and energy consumption by considering the key factors that influence the shape of the heat demand profile.

Figure 4-1 shows the structure of this chapter. This figure describes the links between the measured data from several trials in the UK, and the creation of models to derive the shape of half-hourly heat production and energy demand of four individual heating technologies: ASHP, ground source heat pump (GSHP), natural gas/hydrogen boiler, and resistance heater. In addition, a method to create profiles for district heating was derived from the GSHP model. This chapter will describe the methods that were used for each of these tasks.

Two decarbonisation pathways will be defined for the case studies in Cardiff, Swansea and Newport. The models that are developed will be used to synthesise half-hourly heat production and energy demand based on the heat demand from the dwelling categories that were described in Chapter 3 and assumptions regarding the uptake of different heating technologies.

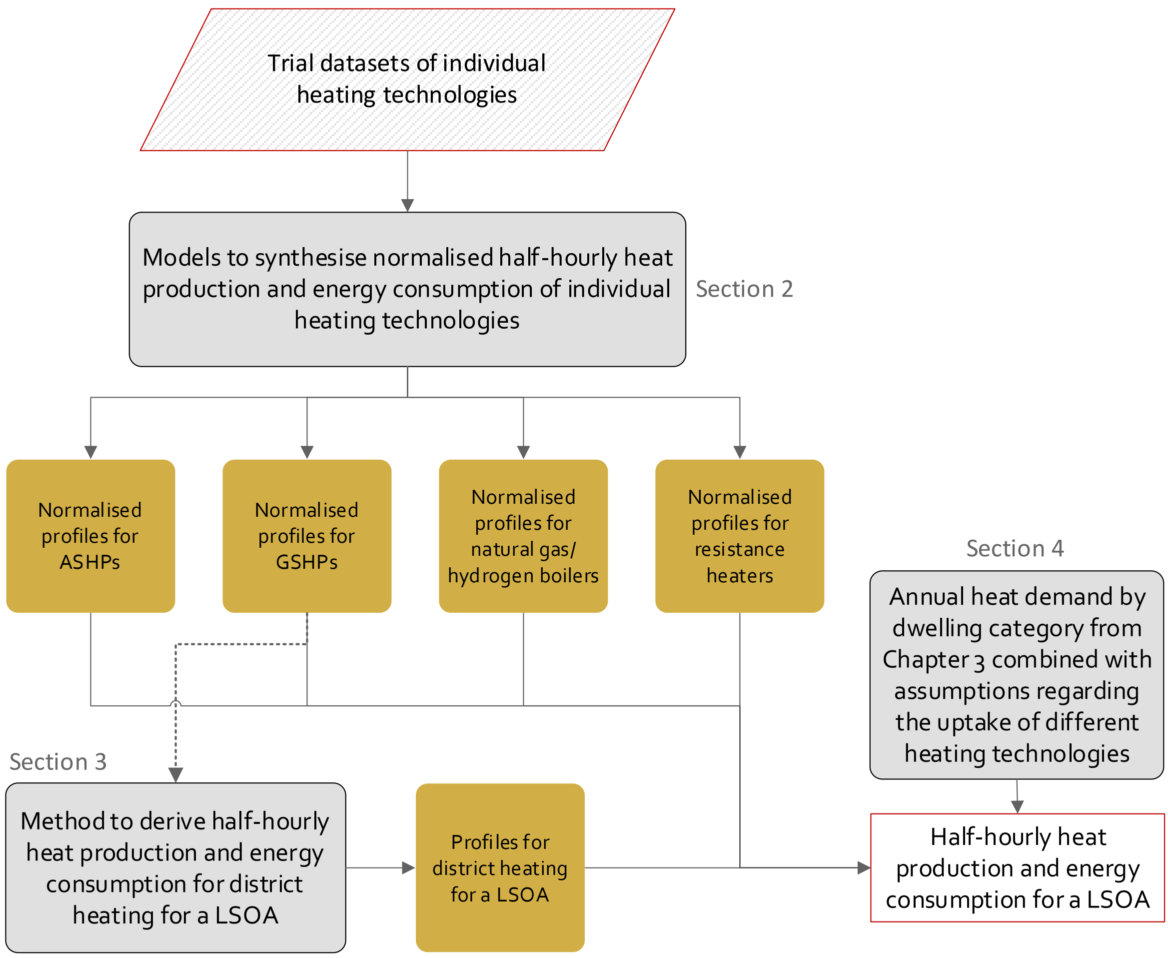


Figure 4-1: Structure of this chapter

4.2 Models to Synthesise Normalised Half-hourly Heat Production and Energy Demand of Individual Heating Technologies

Four heating technologies were considered in this study: ASHPs, GSHPs, gas/hydrogen boilers and resistance heaters. A machine learning algorithm was used to develop a model to synthesise half-hourly heat production. For each heating technology, a model was developed to synthesise half-hourly energy demand. The models were trained using time series data from domestic heating trial projects considering the most influential factors, including time and outside air temperature (OAT). The heat production and energy demand data of the trial projects were analysed before creating the models to understand the characteristics of each heating technology.

4.2.1 Methodology to Create the Models

Figure 4-2 shows an overview of the steps followed to create the machine learning models for each heating technology. The same approach was used for the models that synthesised half-hourly heat production and the models that synthesised half-hourly energy demand. The steps involved:

1. Pre-processing of measured data from trials. More details of this step were given in the section discussing the input data to the machine learning models (see Section 4.2.2.1).
2. Selecting of independent variables that have a significant influence on the target variable (heat production or energy demand). Creating of the model and calibrating of the hyperparameters of the model using a cross-validation procedure to improve accuracy using the original trial datasets. In machine learning, a hyperparameter is a parameter whose value is used to control the learning process. A cross-validation procedure is a testing procedure used to test and validate the effectiveness of a machine learning model. The most common approach, used in this study, consists of splitting the original dataset into 5 partitions, with each partition carrying 20% of the data. Data in 4 of the partitions is used to train the model and data in the remaining partition is used to test it. For each combination of training/testing partitions, the performance of the model is calculated and assessed. In this step, the original trial data is considered the ground truth.
3. Testing of the performance of the model.

The extreme gradient boosting algorithm that is implemented in the XGboost library [61] was used to develop these models in Python. A gradient boosting algorithm is based on an ensemble method where the results of several models are combined into one by minimising a loss function using a gradient descent algorithm. XGboost is an implementation of this algorithm, which combines predictions from several decision trees with a gradient boosting algorithm [61], and can be used to predict continuous or categorical data. There are other machine learning algorithms that could have been used to get similar or potentially better performances. The XGboost library was chosen because of its recognition in data science competitions and its large community of users.

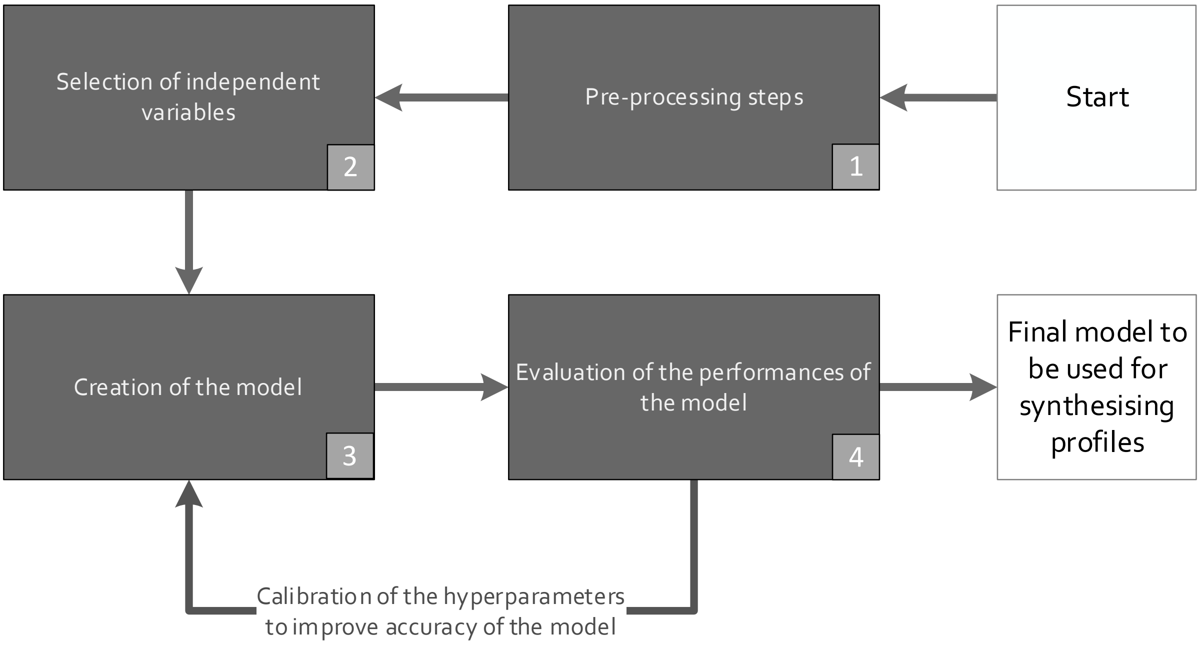


Figure 4-2: Steps to create the machine learning models that are used in this study.

The variables common to all the models created in this study include:

- The half-hour of the day,
- The day of the week,
- The month of the year,
- The daily average OAT,
- The target variable (the half-hour heat production or energy demand).

For the case of heat pumps (HPs), for which the COP is impacted by the OAT, the approach shown in Figure 4-3 was used to synthesise the energy demand profile. A first model (HP_{heat}) was created to synthesise the heat production profile (block 1) using the list of variables described previously. The profile produced with HP_{heat} was used as an additional feature of a second model ($HP_{electricity}$) (block 2), to synthesise the electricity demand profile. Besides this additional feature, the $HP_{electricity}$ model was created following the same process as the HP_{heat} model.

When producing the data, if the COP is below 1, the electricity prediction is set to be equal to the heat prediction divided by the average daily COP of the trial datasets, 2.6 for ASHPS and 2.75 for GSHPS.

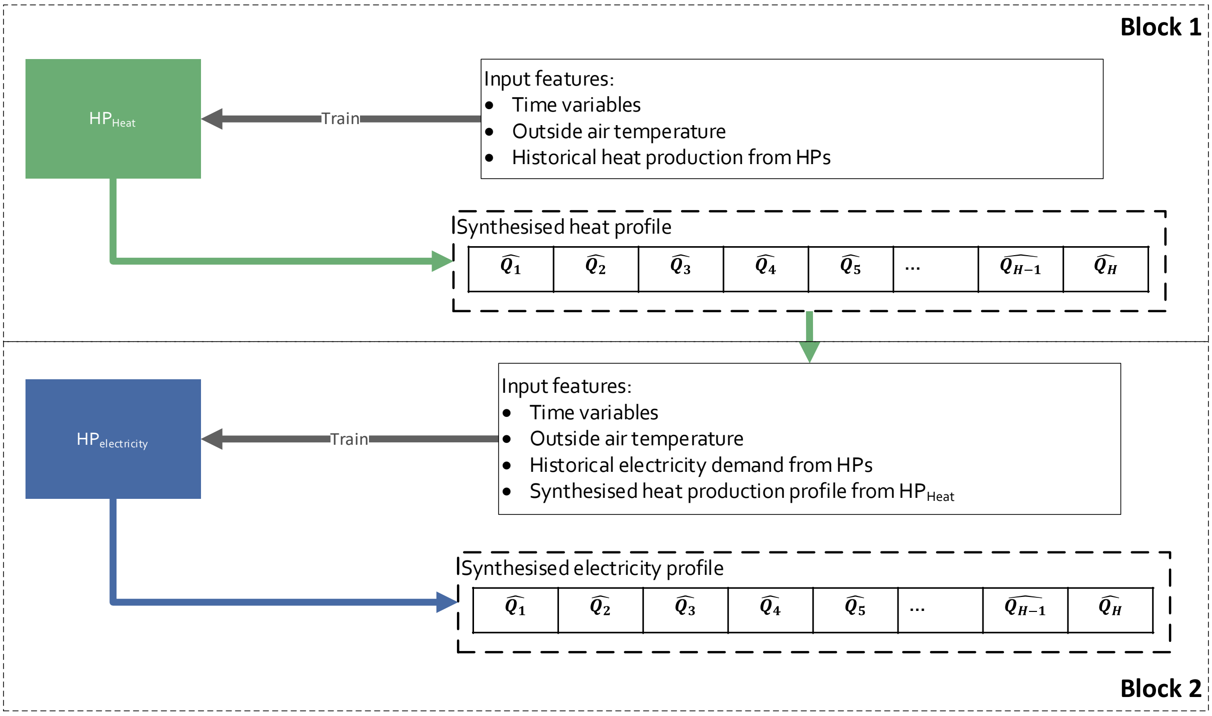


Figure 4-3: Process to produce half-hourly electricity consumption and heat production for HPs with two distinct models HP_{heat} and $HP_{electricity}$

In this study, an ensemble approach was used to create the model in Step 3 (Figure 4-2) where the predictions from different sub-models were combined to improve the accuracy of the final predictions.

Figure 4-4 shows an example of this approach with two sub-models: the *Main model* and an additional *Model 99*. These models were used to predict the values of a target variable, either heat production or energy demand data. The *Main model* was trained on the entire dataset, while *Model 99* was trained on a subset of the dataset that only included the target variable values above the 99th percentile (other values were set to zero). When the predictions from the *Main model* were lower than the predictions from *Model 99*, they were replaced by the predictions from *Model 99*. This was done to improve the predicted peak heat production and peak energy demand. The results are referred to as combined predictions.

On its own, the *Main model* provided an accurate estimate of the total heat production or energy demand (less than 1% error), but the peak was underestimated by 6% to 17% (see Appendix D.4). To improve the performance of the method to predict peak heat production and energy demand, five sub-model combinations were tested following the approach described in Figure 4-4, the combinations follow:

1. *Main model* + *Model 99*;
2. *Main model* + *Model 95*;

3. *Main model* + *Model 90*;
4. *Main model* + *Model 95* + *Model 90*; and,
5. *Main model* + *Model 99* + *Model 95*.

Model 95 refers to a model trained with heat production values above the 95th percentiles. *Model 90* refers to a model trained with values (energy demand or heat production) above the 90th percentiles.

The performances of the models synthesising heat production and the models synthesising energy demand for each technology were analysed using two metrics calculated during the cross-validation procedure:

- The first metric is total heat produced, or energy consumed (the area under the curve).
- The second metric is the coincidental peak for values above the 99% percentile. This error is calculated by comparing the model values in the synthesised dataset with values in the original trial dataset at the same timesteps. The timesteps are drawn from the values of the original dataset above the 99th percentile.

The model synthesising heat production and the model synthesising energy demand with the lowest errors on the two metrics were selected and used in this study.

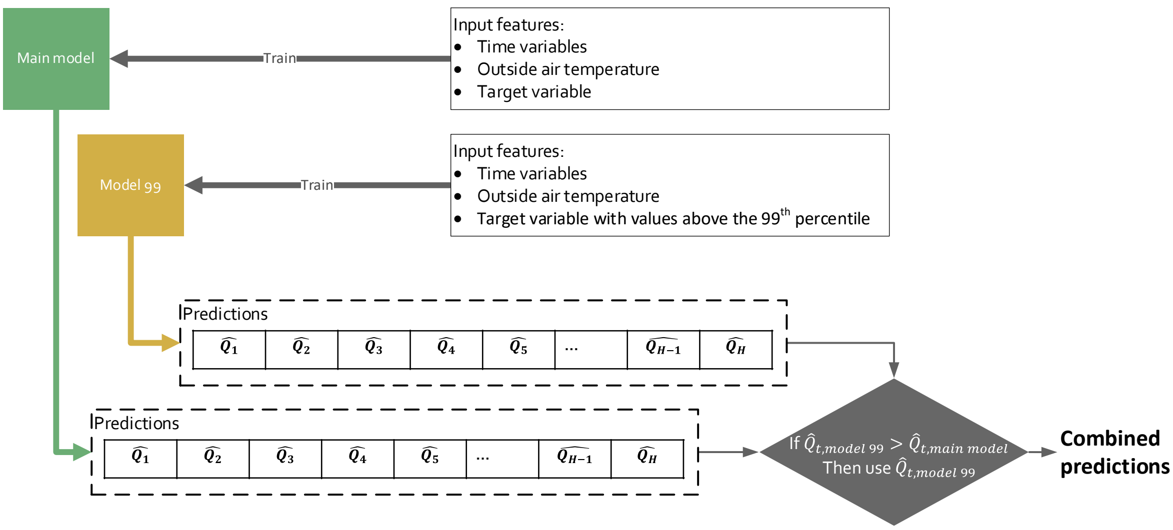


Figure 4-4: Flow chart of an example model that combines the predictions of two sub-models to improve the accuracy in predicting peaks. $\hat{Q}_t$ *is the predicted value of a model for time t with t=1,2,…, H.*

The final synthesised half-hourly heat production and energy demand were normalised. For example, the sum of the values of the synthesised heat production values were equal to one while the synthesised energy demand was normalised based on the synthesised half-hourly heat production to maintain the conversion efficiency factor of each technology. If a group of heat pumps is producing 50 kWh of heat using 25 kWh of electricity and the normalised heat production value is 0.25, the normalised electricity demand value will be 0.125.

4.2.2 Data Analysis and Creation of the Machine Learning Models

4.2.2.1 Input Data to the Machine Learning Models

A dataset of half-hourly aggregated average heat production and energy demand from dwellings for each of the four heating technologies was used to test and train the machine learning models. All the data manipulation was performed using Python.

Collection of the data

Four datasets from trial projects were used in this study. These datasets include records from heat production and electricity demand data of ASHPs, GSHPS and resistance heaters, as well as gas demand data of gas boilers. Table 4-1 shows information regarding the trial datasets the number of dwellings recorded, the geographic area and the duration of the metering.

*Table 4-1: Details of the trial datasets for each technology used in this project. RHPP: Renewable Heat Premium Payment scheme, EDRP: Energy Demand Research Project. *this column gives the number of dwellings recorded for each time step of the dataset.*

Heating technologies	Sources	Number of dwellings with data recorded*	Geographic area	Duration of the metering	Type of dwellings	Granularity of the original data
ASHPs	RHPP scheme [62]	29 to 251	UK	01/10/2013 to 28/02/2015	Social housing	2min
GSHPs	RHPP scheme [62]	11 to 78	UK	01/10/2013 to 30/09/2014	Social housing	2min
Gas boilers	EDRP [63]	8,711	UK	01/07/2009 to 30/09/2010	18 types of households representing different UK customers	30min
Resistance heaters	EDRP [63]	14,615	UK	01/06/2009 to 31/06/2010	18 types of households representing different UK customers	30min

Creation of the half-hourly profiles

For resistance heaters, some preliminary steps were required to calculate the half-hourly electricity demand for heating. The Energy Demand Research Project published electricity demand at half-hourly resolution for 14,000 dwellings from early-2008 to the end of 2010. No information was provided regarding the type of heating system in each household. Hence, to determine if a household was using resistance heaters or not, the average daily electricity demand in summer and winter were compared. If the demand in winter was at least two times higher than in summer, then the household was considered to be electrically heated. Two separate sub-datasets were created, a dataset for electrically heated households (3,367 dwellings) and a dataset for households that used other energy carriers than electricity for heating (10,952 dwellings). The difference between the average aggregated half-hourly electricity demand of these sub-datasets was used to represent a half-hourly profile of the electricity used by resistance heaters for heating.

For the ASHPs, GSHPs and gas boilers, the datasets were directly used to create aggregated average half-hourly heat production and energy demand of these heating technologies.

The UK daily average outside air temperature (OAT) data from the BMRS website [64] was also added to the profiles. This data is produced by National Grid and used for their electricity demand forecasts. No manipulation of this data was performed.

Cleaning of the half-hourly profiles

In terms of cleaning procedure, the aggregated average profiles for ASHPs and GSHPs were cleaned using a rolling z-score on the heat production data with a window size of 24. Entries with an absolute z-score above 3 were removed from the dataset. Further data was removed manually. For ASHPs, in total 338 entries were removed from the training dataset. For GSHPs, in total 146 entries were removed from the training dataset. For gas boilers and resistance heaters, no procedure was performed to clean the data.

Table 4-2 shows the number of entries in the final datasets.

Table 4-2: Number of entries in the datasets for each heating technology

Heating technologies	Number of entries in the dataset
ASHPs	24,430
GSHPs	17,393
Gas boilers	21,936
Resistance heaters	18,192

4.2.2.2 Heat Pumps

4.2.2.2.1 The Trial Dataset for Heat Pumps

[62]The key characteristics of the heating systems that were used in the trial dataset for ASHPs and GSHPs are summarised below:

- ASHPs are installed in detached, terraced and semi-detached houses;
- GSHPs are installed in detached and semi-detached houses;
- The average capacity installed of ASHPs is 8.1 $kW_{thermal}$;
- The average capacity installed of GSHPs is 8.2 $kW_{thermal}$;

- Large HPs (>12 $kW_{thermal}$) are installed in detached houses; and,
- ~50% out of the 82 dwellings for which information regarding backup heaters is available do not have a backup heater.

The limitations of this dataset have been discussed in [45] and include:

1. A high number of social houses in the dataset;
2. HPs were installed as a retrofit measure in dwellings with basic energy efficiency measures in place;
3. The electricity demand measurements of the HPs are uncertain because it may include a booster heater and circulation pump;
4. The low number of GSHPs monitored;
5. The difference in the mean capacity of HPs in the dataset compared to those in the market; and,
6. For this research, another limitation that was identified is that the daily average OAT of the UK did not drop below 0.9°C during the recorded period, which is a challenge when modelling the performance of HPs for lower OAT.

Despite these limitations, this dataset offered the best real data that is currently available in GB to estimate the aggregate load profile of HPs. See Appendix D.1 for a snapshot of the dataset.

The dataset was analysed to extract knowledge about the performance of ASHPs and GSHPs with the changes of the OATs. Additional data was generated to mimic the operation of HPs during cold temperatures to overcome limitation number 6 (see following Section 4.2.2.2.4).

4.2.2.2.2 The Average Half-hourly Electricity Demand of ASHPs and GSHPs

Averaged half-hourly electricity demand of the HPs in a typical and in the coldest winter day is shown in Figure 4-5 and Figure 4-6.

Figure 4-5 shows that for ASHPs, the winter electricity demand has a peak in the morning at around 7 am and a second, slightly lower, peak in the afternoon/evening. The coldest day follows a similar pattern, but the overall electricity demand is consistently higher.

Figure 4-6 shows that for GSHPs, the profiles are similar to the ASHPs' patterns. However, the performance of the GSHPs is less sensitive to OAT, thus the electricity demand profile for the coldest day is not very different from the profile of the typical winter day (total electricity demand on the coldest day is slightly higher than the electricity demand on the average winter day).

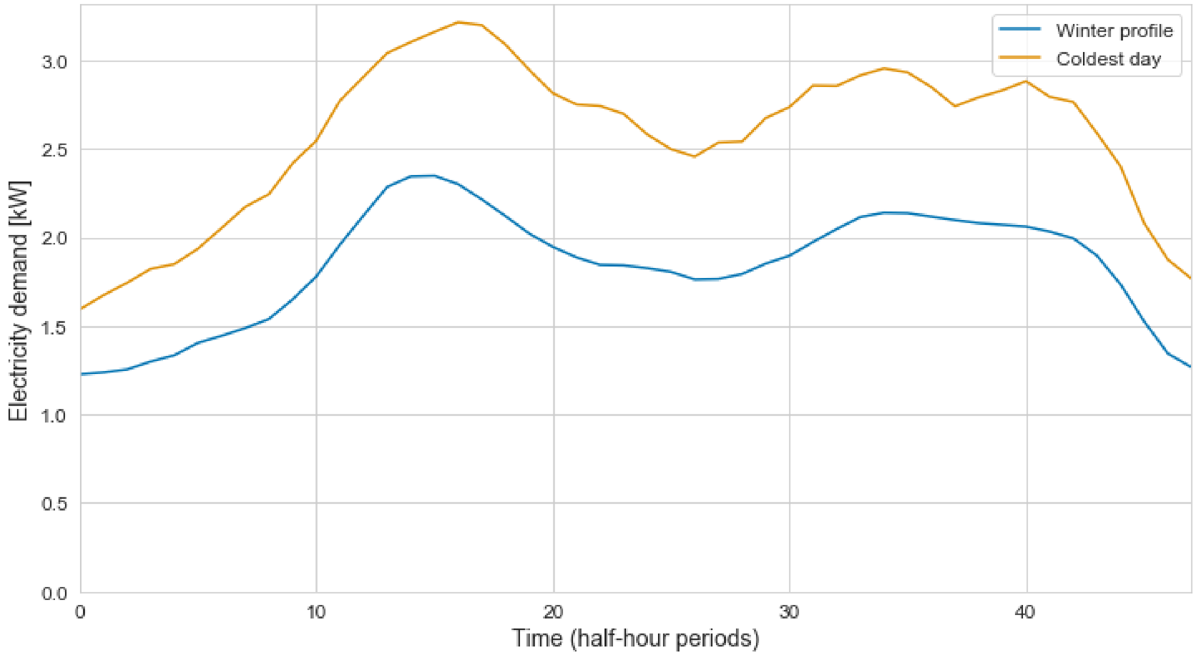


Figure 4-5: Average half-hourly electricity demand of ASHPs smoothed using a three-half-hourly period centred window moving average (the smoothing average was used for visualisation purposes only).

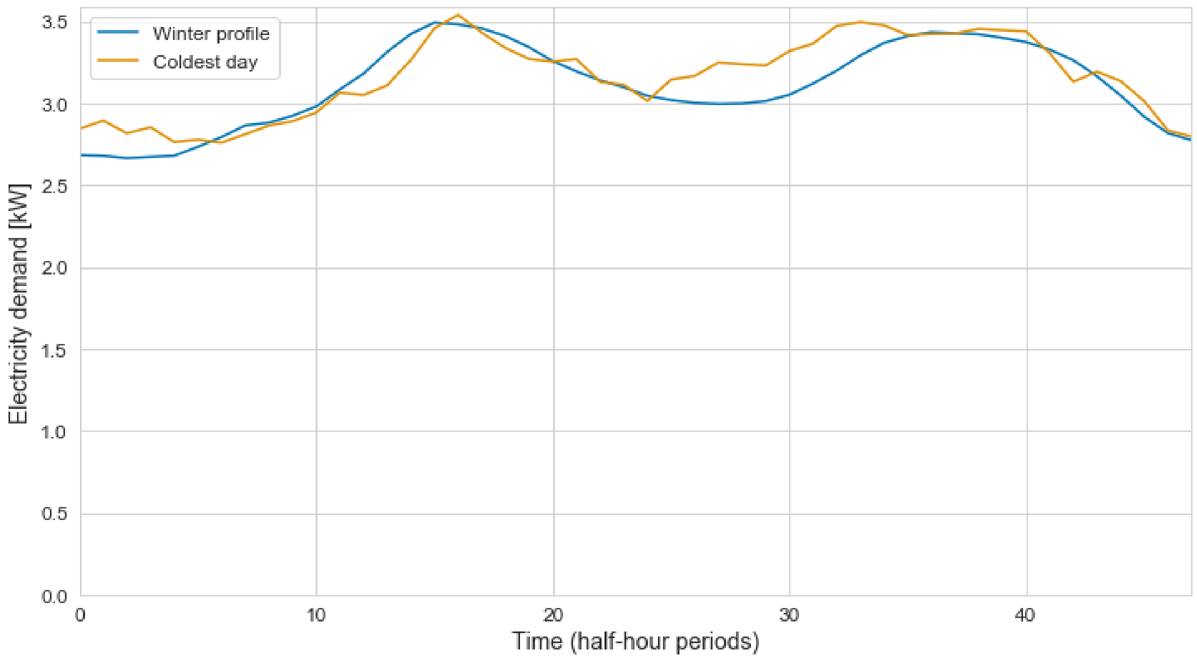


Figure 4-6: Average half-hourly electricity demand of GSHPs smoothed using a three-periods centred moving average.

4.2.2.2.3 Relationship Between the Coefficient of Performance (COP) of Heat Pumps and Outside Air Temperature

The COP is the ratio between the heat produced and the electricity consumed by a HP. It quantifies the efficiency of a heat pump at transferring heat from a heat source to a heat sink. The COP depends on the temperature difference between the heat source and the sink, and also can vary from heat pump types, size and manufacturer.

The COP of individual HPs was calculated every 30 minutes in the dataset by calculating the ratio between heat production and electricity demand. Outliers were removed from the dataset (we defined an outlier as a record where the COP is below one or above 5 over a 30min period). The average COP for every time step was then calculated using the following formula:

$$\widehat{COP_t} = \frac{\sum_{k=1}^{n} COP_t^k}{n} \tag{2}$$

Where COP_t^k is the COP of heat pump k at time t, and n is the number of HPs with COP data at time t.

Figure 4-7 and Figure 4-8 shows the distribution of the COP of the individual ASHPs and GSHPs in the dataset. COPs of individual HPs are provided in Appendix D.3.

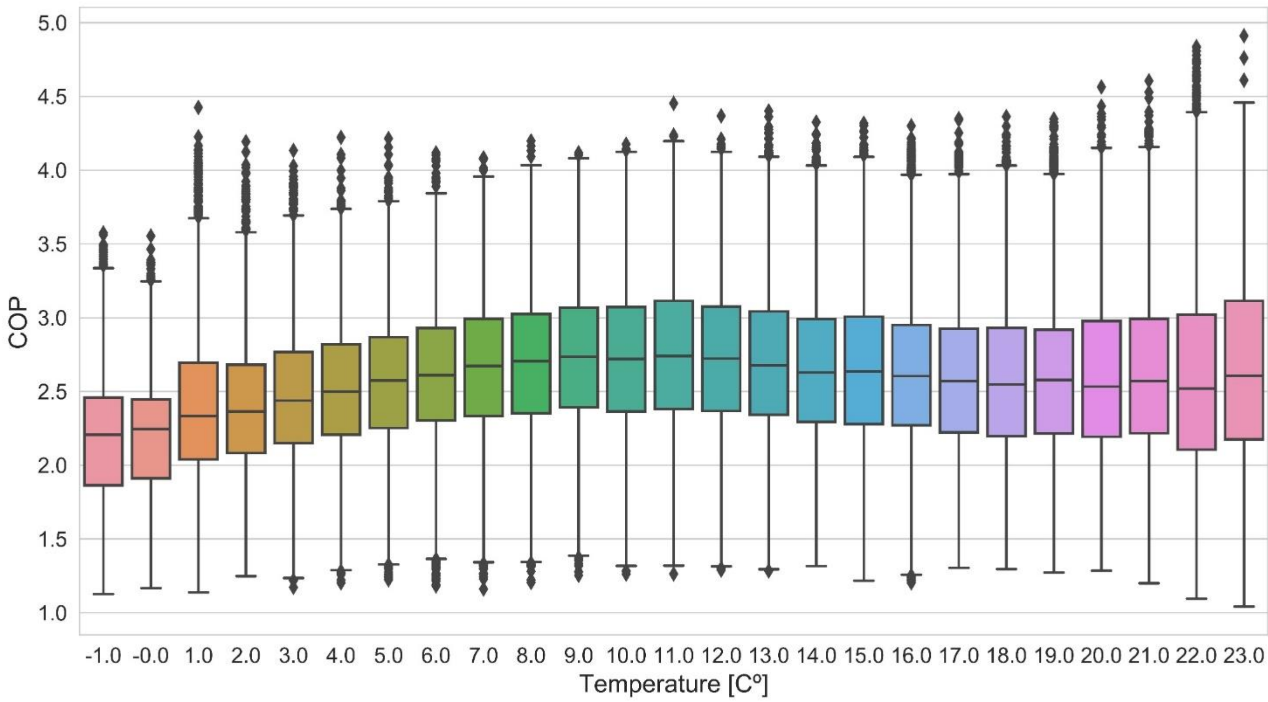


Figure 4-7: Boxplots showing the distribution of the COP of ASHPs against daily average OAT

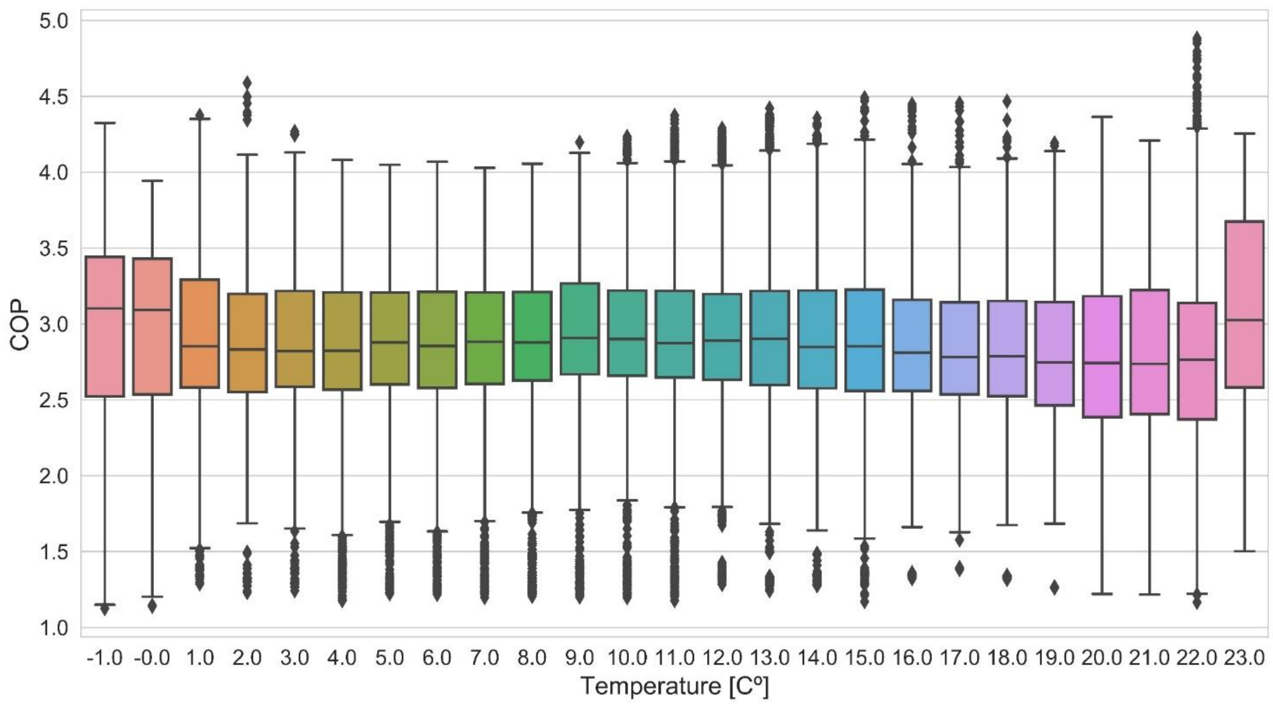


Figure 4-8: Boxplots showing the distribution of the COP of GSHPs against daily average OAT

Figure 4-9 and Figure 4-10 show the relationship between the average daily COP for ASHP and GSHP, and the UK daily average OAT. The normalised min-max daily heat production is also plotted. These figures show that:

- The COP of GSHPs is less sensitive to outside daily temperature compared to the COP of ASHPs; and,
- The drop in COP when the daily average OAT is above 15°C is due to the reduced efficiency of HPs during part-load operation [65].

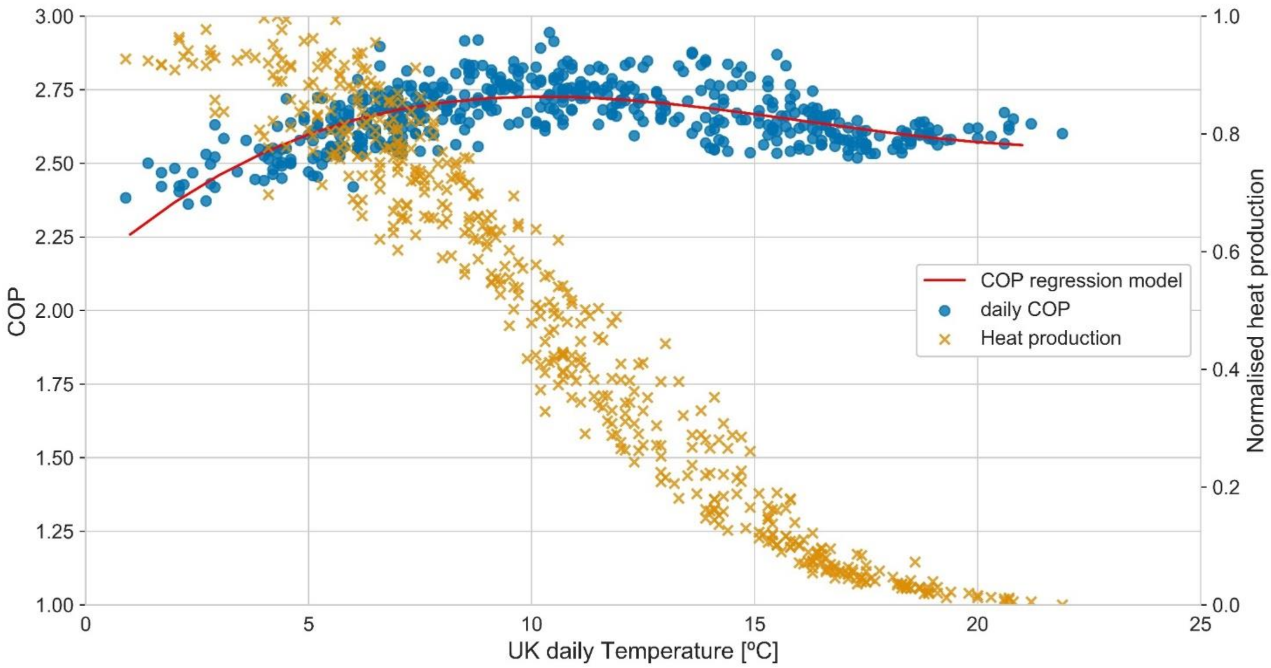


Figure 4-9: COP and normalised heat production against UK daily average OAT for ASHP

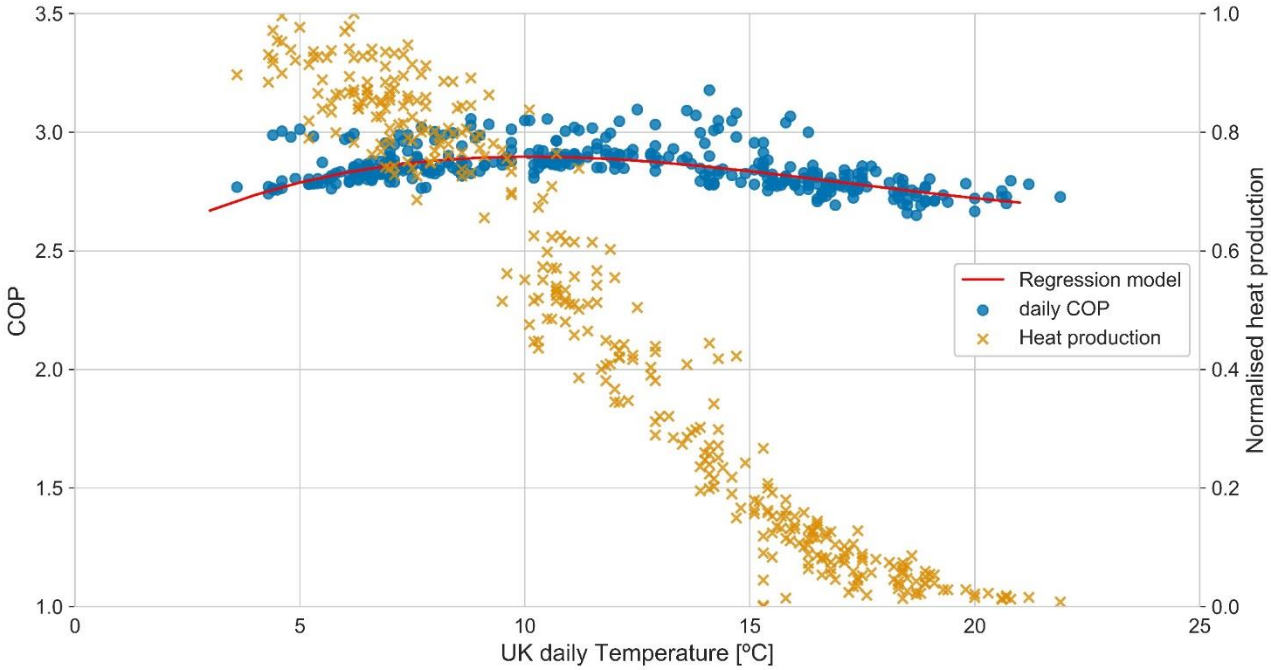


Figure 4-10: COP and normalised heat production against UK daily average OAT for GSHP

A regression curve using a Huber loss function[5] was fitted on the COP data to describe the relationship between the COP and the daily average OAT. The equations obtained are as follows:

$$ASHP_{COP} = 2.1302 + 0.1377 \times T - 0.0098 \times T^2 + 0.0002 \times T^3, \forall T > 1°C \quad (3)$$

$$GSHP_{COP} = 2.3887 + 0.1166 \times T - 0.0082 \times T^2, \forall T \geq 4°C \quad (4)$$

4.2.2.2.4 Heat Production and Electricity Demand Data for HPs During Cold Temperatures

In the original dataset, there is no heat production or electricity demand data for HPs where daily average OATs are below zero. Therefore, the specifications for heat pump installers in GB from the Microgeneration Installation Standard (MIS 3005) [66] and the expected performance of HPs described in the literature were used to create additional heat production and electricity demand data and extend the original dataset. This enabled the models trained with this data to synthesise the heat production and energy demand of HPs during cold temperature. Half-hourly heat production from HPs and their COP, as well as half-hourly heat production from backup heaters were synthesised for a range of daily average OATs from ~-8˚C to ~+4˚C. This included the daily average OAT of -4.2˚C, which was considered to be the temperature in 1-in-20 peak winter day[6] in South Wales.

According to the MIS 3005, a heat pump should be able to cover 100% of the space heating demand when the OAT is above the *outside design temperature*. The outside design temperature is defined according to the location of the installation. For instance, in Cardiff, the outside design temperature is -3.2˚C. Below this temperature, a backup heating system is required to cover the additional heat demand (or a bigger heat pump can be installed). This is illustrated in Figure 4-11.

---

[5]The Huber loss function is robust to outliers by combining a quadratic and a linear loss function, which was used to extract the general trend from the measured data and minimise the impacts of outliers.

[6] The gas network operators use the 1-in-20 peak winter day methodology to quantify the demand on a winter day that statistically occurs once every 20 years. This is the demand that could occur during very cold winter days. Gas network companies design their infrastructure to be able to supply such a demand. Given that a significant amount of heat may be electrified in the future, in this project this methodology was also applied to the electricity network. Therefore, it was crucial to be able to estimate 1-in-20 peak winter day demand for gas/hydrogen and electricity-based technologies.

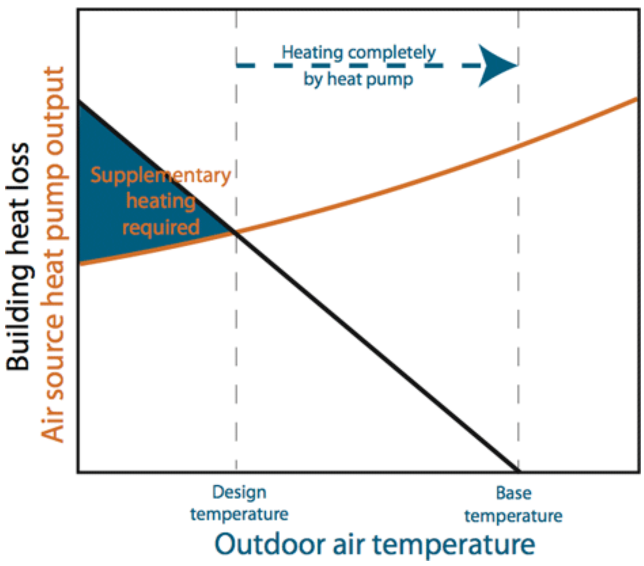


Figure 4-11: Operation of an ASHP and supplementary heat source at various OATs (source: figure from [67])

Figure 4-12 shows the relationship between the COP for ASHPs and OAT at various flow temperatures of the water entering the central heating system of the dwelling. This assumes constant heat demand and thus does not account for the impacts of customers behaviours and different controls. Based on this figure, the COP for ASHPs was considered to decrease linearly with OAT as the temperature falls below 2°C. Similarly, a linear relationship between the COP of GSHPs and the OAT was assumed. However, the OAT is expected to have minimal impact on the COP of GSHP (see Equation 4).

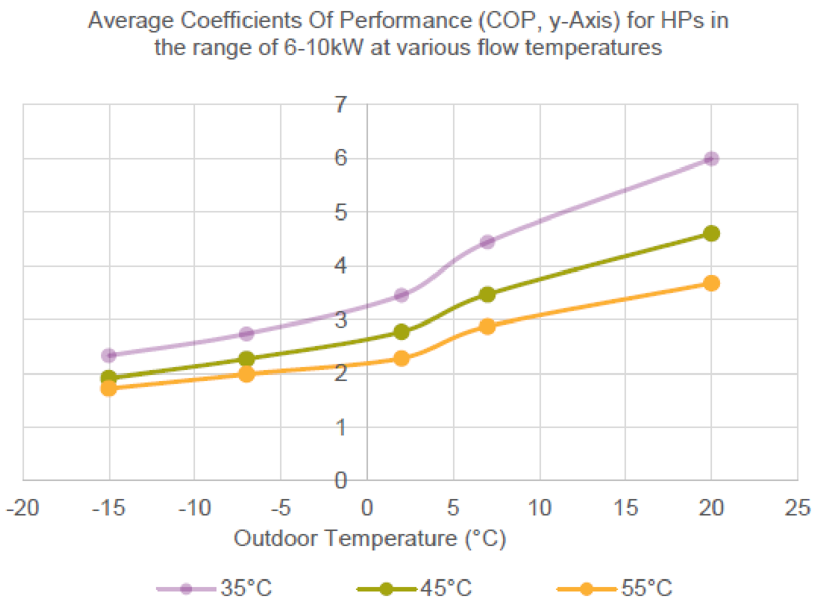


Figure 4-12: Changes in COP against OAT and supply temperature (source: figure from [36])

Figure 4-13(a) shows the COP in the original data and the new data for ASHPs. The green dots represent the new values of the daily COP, which were extrapolated from the original data points using a linear regression fitted on original COP values (blue dots) below 2°C. The new COP values (green dots) show a similar trend as that given in Figure 4-12. For temperature below 2°C, it was assumed that the increase in heat demand would minimise the difference in customers behaviours and controls and bring the COP of the heat pumps close and thus justify the same type of trend that seen in Figure 4-12.

Figure 4-13(b) shows the real and new data for heat production and electricity demand by ASHPs. Similar to the new COP values, the new data for electricity demand (pink triangles) were produced using linear extrapolation. The new heat production for the ASHPs (pink crosses) was calculated by multiplying the new COP by the new electricity demand. As shown in Figure 4-11, below the design temperature, the ASHPs need to be supported by backup heaters to meet the heat demand. This could be additional resistance heaters or gas boilers. In Figure 4-13(b), the difference between the total heat production (light-blue crosses) and the heat produced by ASHPs (pink crosses) represents the heat that is supplied by backup heaters.

The total heat that is required to be supplied by ASHPs and backup heaters below the design temperature was estimated by linearly extrapolating the heat production of ASHPs between -3.2°C and 5°C.

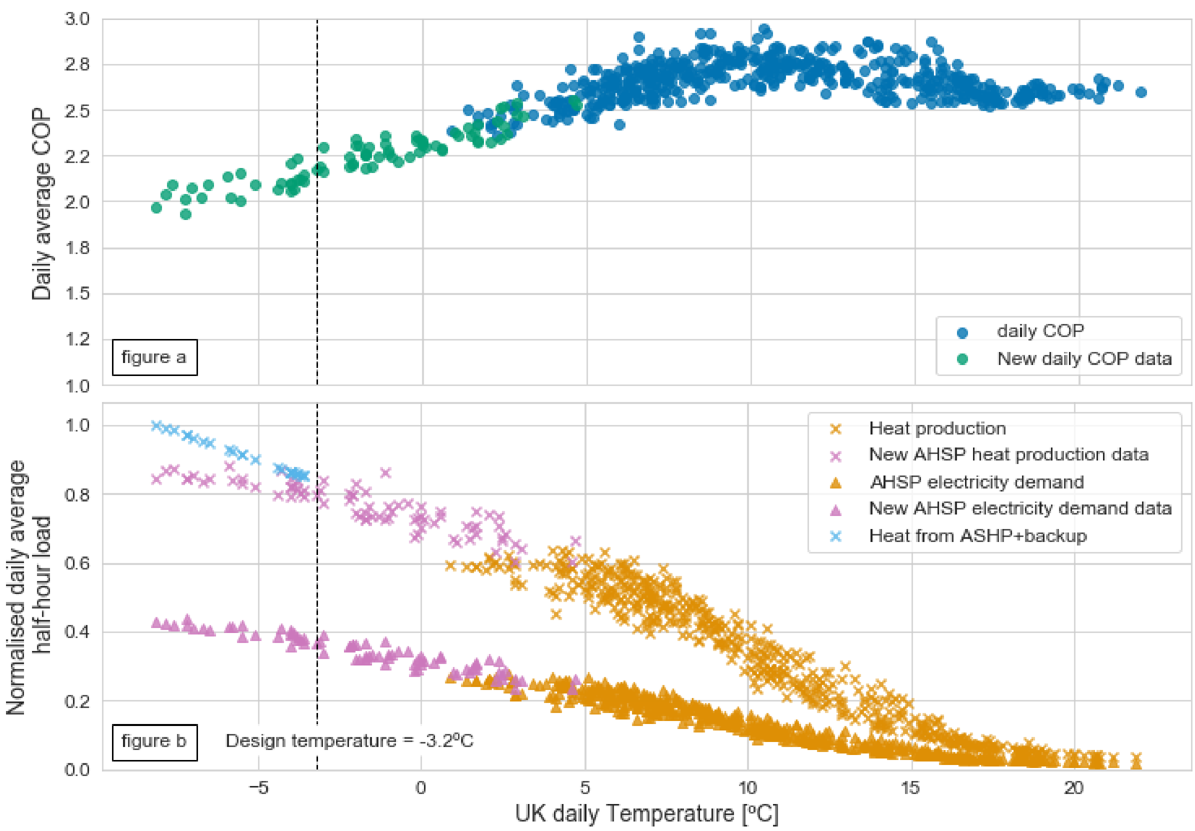


Figure 4-13: Panel a shows the COP related to the operational data from Panel b. Panel b shows the normalised min-max real and new data of heat production and electricity demand of ASHPs against daily average OAT.

Figure 4-14 shows the new data for GSHPs using a similar process as that used for the ASHPs. However, the performance of the GSHPs is less sensitive to outside air temperature, thus the decrease in COP (green dots) with temperature is less acute compared to ASHPs. Consequently, the installation of backup heaters is less likely for GSHP based systems.

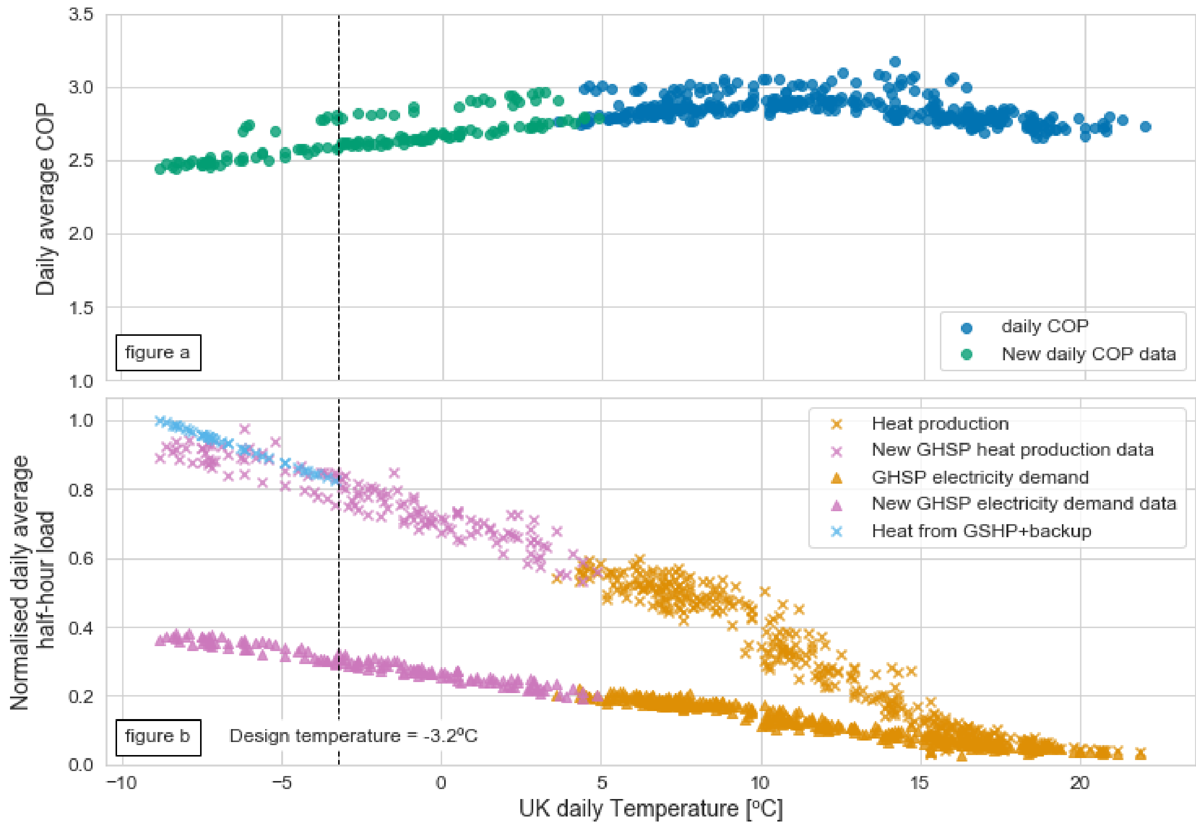


Figure 4-14: Panel a shows the COP related to the operational data from Panel b. Panel b shows the normalised min-max real and new data of heat production and electricity demand of GSHPs against daily average OAT.

4.2.2.2.5 Creation of machine learning models for ASHPs

The half-hourly heat production and electricity demand data was used to create the models using the methodology that was described in Section 4.2.1.

The $ASHP_{heat}$ model selected combined the *Main model*, *Model 95* and *Model 90*. Compared to the original data, it shows:

- An error of 1% for the heat produced (the area under the curve); and,
- An error of -9% for the coincidental peak for values above the 99% percentile.

The $ASHP_{electricity}$ model that was selected combined the *Main model, Model 95 and model 90.* Compared to the original data, it shows:

- An error of 1% for the electricity demand (the area under the curve); and,
- An error of -5% for the coincidental peak for values above the 99% percentile.

The models were then retrained with the extended dataset, including the original dataset and the synthesised operational data for cold OAT. Tables showing the performance of all of the models created for ASHPs are available in Appendix D.4.

Figure 4-15 shows the normalised min-max half-hourly electricity demand of ASHPs for 2018 UK daily average OATs, synthesised using the $ASHP_{heat}$ and $ASHP_{electricity}$ selected models.

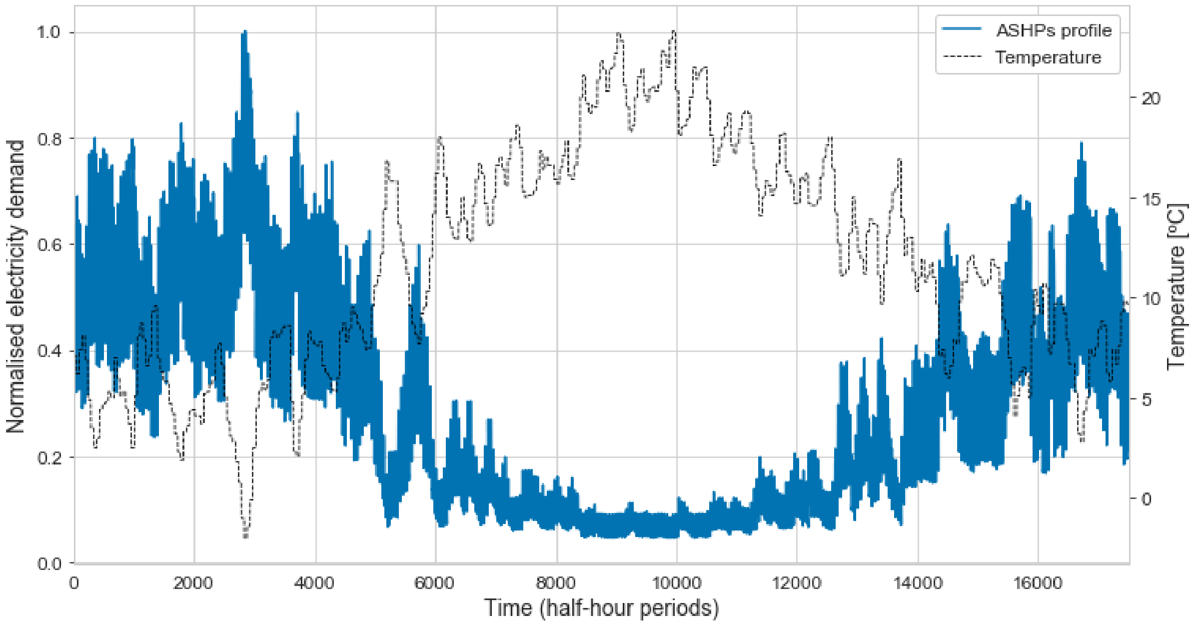


Figure 4-15: Max-min normalised electricity demand of ASHPs synthesised using the UK 2018 daily average OATs.

Figure 4-16 shows the average electricity demand of an ASHP in a detached house for a daily average OAT of +5.7°C (a typical winter day) and -4.2°C (a cold winter day) synthesised using the $ASHP_{heat}$ and $ASHP_{electricity}$ models. When the daily average OAT is +5.7°C, the after diversity ASHP peaks in the morning at ~1.2 kW. Backup heating is not required, thus its output is kept at 0 kW for the entire day. At -4.2°C, the ASHP follows the same pattern but peaks at 2.6 kW and the backup heating consumes electricity to provide the additional heat that cannot be provided by the ASHP because it was sized for an OAT of -3.2°C. The profiles synthesised using the models are after-diversity profiles as the training data represents average profiles from a large number of units.

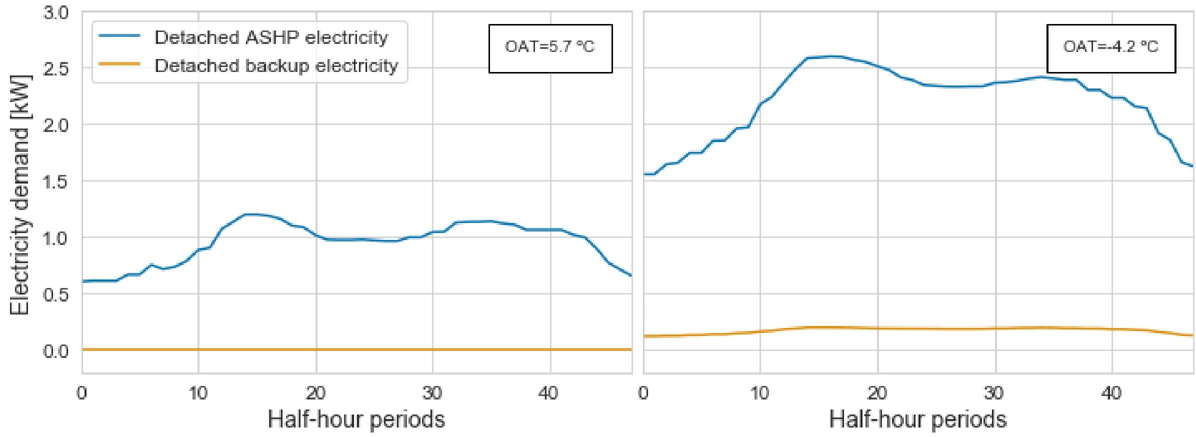


Figure 4-16: Electricity demand (after diversity) for an ASHP installed in a detached house. The chart on the left-hand side is for an average daily OAT of +5.7°C. The ASHP consumes 46 kWh of electricity and the backup heater zero for total heat production of 115 kWh. The chart on the right-hand side is for an average daily OAT of -4.2°C. The ASHP consumes 105 kWh of electricity and the backup heater 8 kWh for total heat production of 228 kWh.

4.2.2.2.6 Creation of Machine learning models for GSHPs

The same method described for ASHP was used to produce the GSHP models.

The $GSHP_{heat}$ model selected combined the *Main model and Model 90*. Compared to the original data, it shows:

- An error of 1% for the heat produced (the area under the curve); and,
- An error of -6% for the coincidental peak for values above the 99% percentile.

The $GSHP_{electricity}$ model selected combined the *Main model and Model 90*. Compared to the original data, it shows:

- An error of 0% for the electricity demand (the area under the curve); and,
- An error of -5% for the coincidental peak for values above the 99% percentile.

Tables showing the performance of all the models created for GSHPs are available in Appendix D.4.

4.2.2.3 Natural Gas and Hydrogen Boilers

Hydrogen boilers are based on similar technology to natural gas boilers, and thus it was considered that their gas demand profiles were similar. In the following, the term *gas boiler* refers to hydrogen and natural gas boilers.

4.2.2.3.1 The relationship between gas demand and temperature

The normalised daily gas demand was calculated by aggregating the gas demand from all boilers for each timestep and then resampling the result at daily resolution before normalising it using a min-max procedure. Figure 4-17 shows a scatterplot of the daily gas demand against the daily average OAT. A change-point regression model was fitted on the data, which minimises the RMSE [68]. The change-point regression equation is:

$$Q_{gas} = \begin{cases} 0.8155 - 0.0561 \times T, & \forall T < 14.1℃ \\ 0.0292, & \forall T \geq 14.1℃ \end{cases} \quad (5)$$

The change-point was identified to be 14.1°C; above this daily average OAT, the gas boilers are only used to supply hot water.

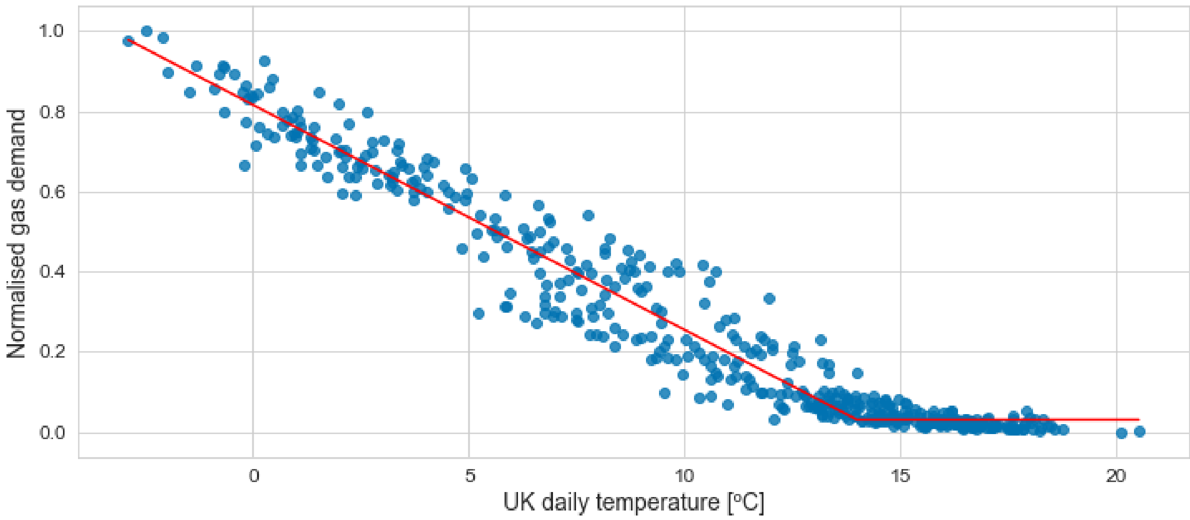


Figure 4-17: The normalised min-max daily gas demand against UK daily average OAT

The dataset was extended to include additional half-hourly gas demand data in the range of daily average OAT of -2°C to -7°C by extrapolating existing data using Equation 5.

4.2.2.3.2 Creation of machine learning models for gas boilers

The models to synthesise half-hourly heat production and gas demand for gas boilers were created using the half-hourly gas demand of the trial dataset and the heat production derived from it assuming a constant efficiency of 84% (regardless of the level of heat output and the OAT) [69].

The $GasBoiler_{heat}$ and $GasBoiler_{gas}$ models that were selected combined the *Main model and Model 95*. Compared to the original data, it shows:

- An error of 1% for the heat produced (the area under the curve); and,

- An error of -1% for the coincidental half-hourly peak for values above the 99% percentile.

4.2.2.4 Resistance Heaters

4.2.2.4.1 The Relationship Between Electricity Demand and Temperature

The half-hourly electricity demand for heat was converted to daily resolution. A change-point regression model was then fitted on this data, as shown in Figure 4-18. The equation that is obtained is:

$$Q_{gas} = \begin{cases} 0.8538 - 0.0581 \times T, & \forall T < 13.7℃ \\ 0.0557, & \forall T \geq 13.7℃ \end{cases} \tag{6}$$

The change-point temperature is lower than for gas-heated buildings (Section 4.2.2.3). This might be explained by the fact that electricity heated households are usually flats or more recent households, and are thus better insulated than gas-heated households. This may be also due to the way to the electricity for heating data was extracted.

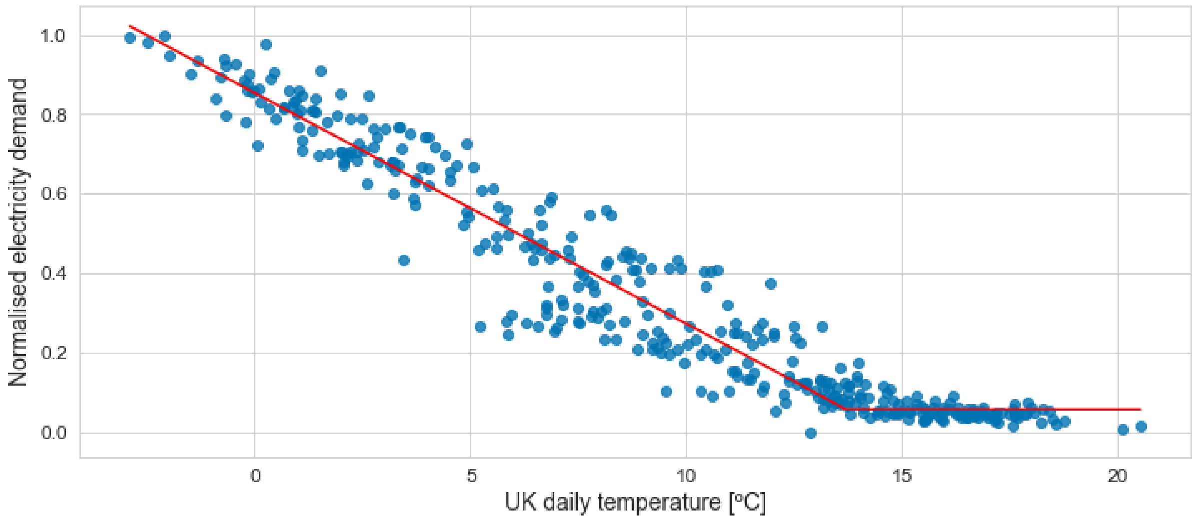


Figure 4-18: Scatterplot of the normalised min-max daily electricity demand against UK daily average OAT

The dataset was extended to include additional half-hourly electricity demand data in the range of daily average OAT of -2°C to -7°C by extrapolating existing data using Equation 6.

4.2.2.4.2 Creation of Machine Learning Models for Resistance Heaters

The efficiency of resistance heaters is equal to 100%, thus the $ElecHeater_{heat}$ and $ElecHeater_{electricity}$ were identical. These two models were trained using the half-hourly electricity demand from the trial dataset.

The $ElecHeater_{heat}$ and $ElecHeater_{electricity}$ models selected combined the *Main model and Model 90*. Compared to the original data, it shows:

- An error of 0% for the heat produced (the area under the curve); and,
- An error of -11% for the coincidental half-hourly peak for values above the 99% percentile. The error is higher than for other models. This might be due to the quality of the original data or the need for a more complex model to capture the variation of the electricity demand for heating.

4.3 Methodology to Synthesise Heat Production and Energy Demand for District Heating

The shape of the half-hourly heat production and energy demand of a district heating scheme is different from individual-heating technologies because of factors such as the use of large-scale thermal storage. In district heating networks, the magnitude of heat production by heat supply units at each time step could deviate from the heat demand of the consumers because of the use of thermal storage and the heat losses in the network.

Figure 4-19 shows the steps to synthesise half-hourly heat production and energy demand of a district heating scheme with thermal storage for a local area (e.g., LSOA). It entails three main steps:

1. Creating the half-hourly heat demand of the consumers connected to the heat network using the model for GSHPs from Section 4.2.2.2.6, which corresponds to a case where no thermal storage was used in the district heating;
2. Sizing the thermal storage based on the half-hourly heat production produced in Step 1 and then producing a new half-hourly heat production considering the heat storage; and,
3. Calculating the capacity and the half-hourly energy demand for each of the heat supply units.

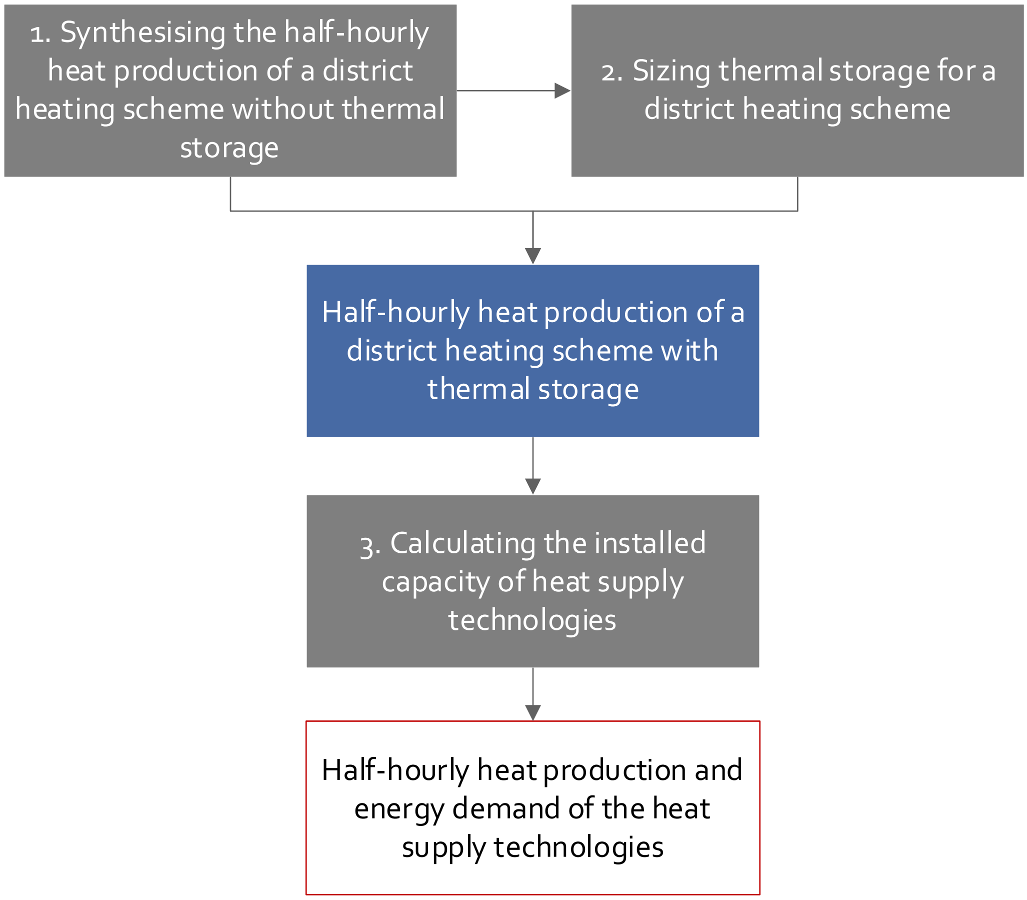


Figure 4-19: Methodology to synthesise half-hourly heat production and energy demand of the heat supply units of a district heating.

4.3.1 Synthesising Heat Production Profile of a District Heating Without Thermal Storage

The heat production profile of a district heating system without thermal storage was synthesised using the GSHP model, $GSHP_{heat}$ (Section 4.2.2.2.6). The annual heat demand for the local area was estimated using the EPC-based method (see Chapter 3). Finally, 8% estimated heat losses from the district heating network [70] was added to scale the profile.

4.3.2 Synthesising the Heat Production Profile of a District Heating Scheme With Thermal Storage

The behaviour of thermal storage in a district heating system can be modelled in many different ways. In this study, the objective of the thermal storage is to decrease the within-day peak heat production, which will enable the heat supply units to have a more constant operation throughout the day by shifting the production from peak time to off-peak time. The losses of the energy stored in the thermal storage (i.e., a large-scale hot water tank) were fixed at 0.2% per day [70].

Figure 4-20 demonstrates the control of a thermal storage unit implemented for a single day. The thermal storage unit is charged during the off-peak period (i.e., 11 pm to 6 am) and discharged during the peak period (i.e., 7 am to 5 pm). At the end of each discharging period, the heat stored in the thermal storage is zero. The size of the thermal storage unit is equal to the maximum heat stored during the day.

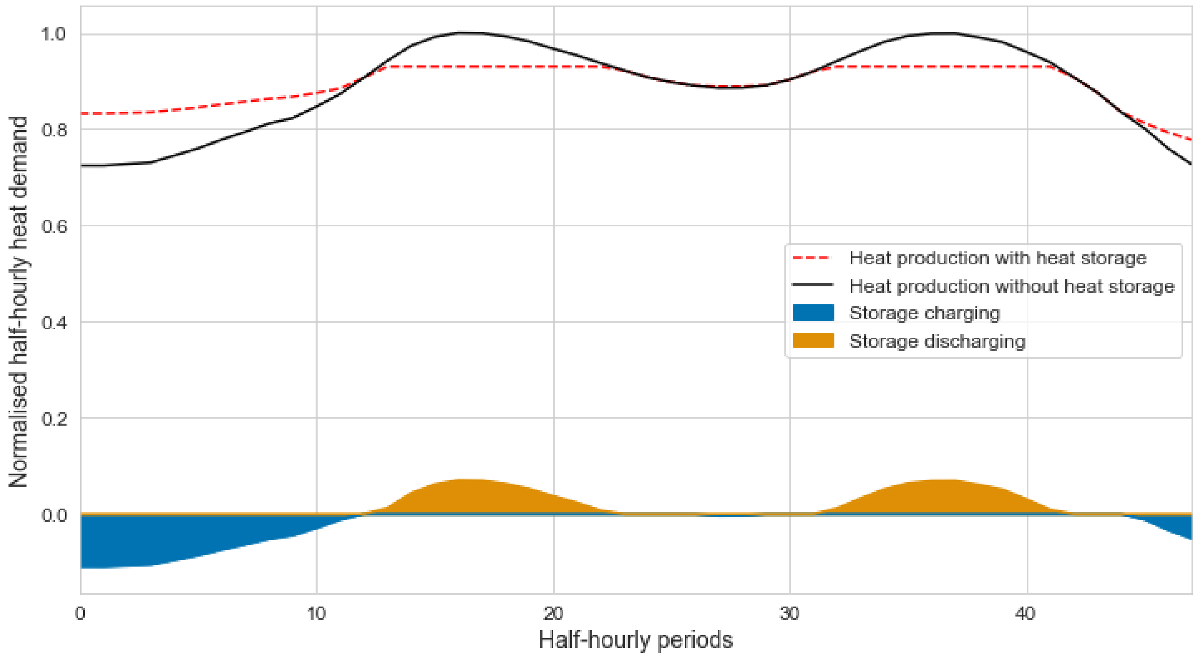


Figure 4-20: Example of the charging and discharging behaviour of a thermal storage unit for a day based on a normalised min-max half-hourly heat production

Figure 4-21 shows the iterative process that is used to determine the size of the thermal storage unit in a district heating network. The process starts by setting a target to reduce the peak heat production. For every day of the year, a charging/discharging profile for the thermal storage unit similar to Figure 4-20 was created. The daily profile with the maximum energy stored was used to calculate the size of the thermal storage unit. If shifting the load within a day in the new heat production profile that considered thermal storage creates a new heat production peak during the off-peak time, then the configuration was rejected and the results from the previous iteration were used; otherwise, the amount of peak heat reduction was increased and the process was repeated.

This process was done for every day of the year because the maximum thermal storage requirement was observed to happen on a different day than on the day where the production was the highest. This happens because the half-hourly heat production profile for a day is flatter than the daily average OAT (which is shown with gas boilers by [30]), which decreases the potential for within-day thermal storage.

The choice to go for the largest thermal storage possible was driven by an analysis showing that the lowest overall costs of a district heating system were achieved by maximising the size of the daily thermal storage unit (see Appendix E). Supplying one-third of the domestic heating demand for Cardiff (~500 GWh) would require a water thermal storage of ~8000 m^3.

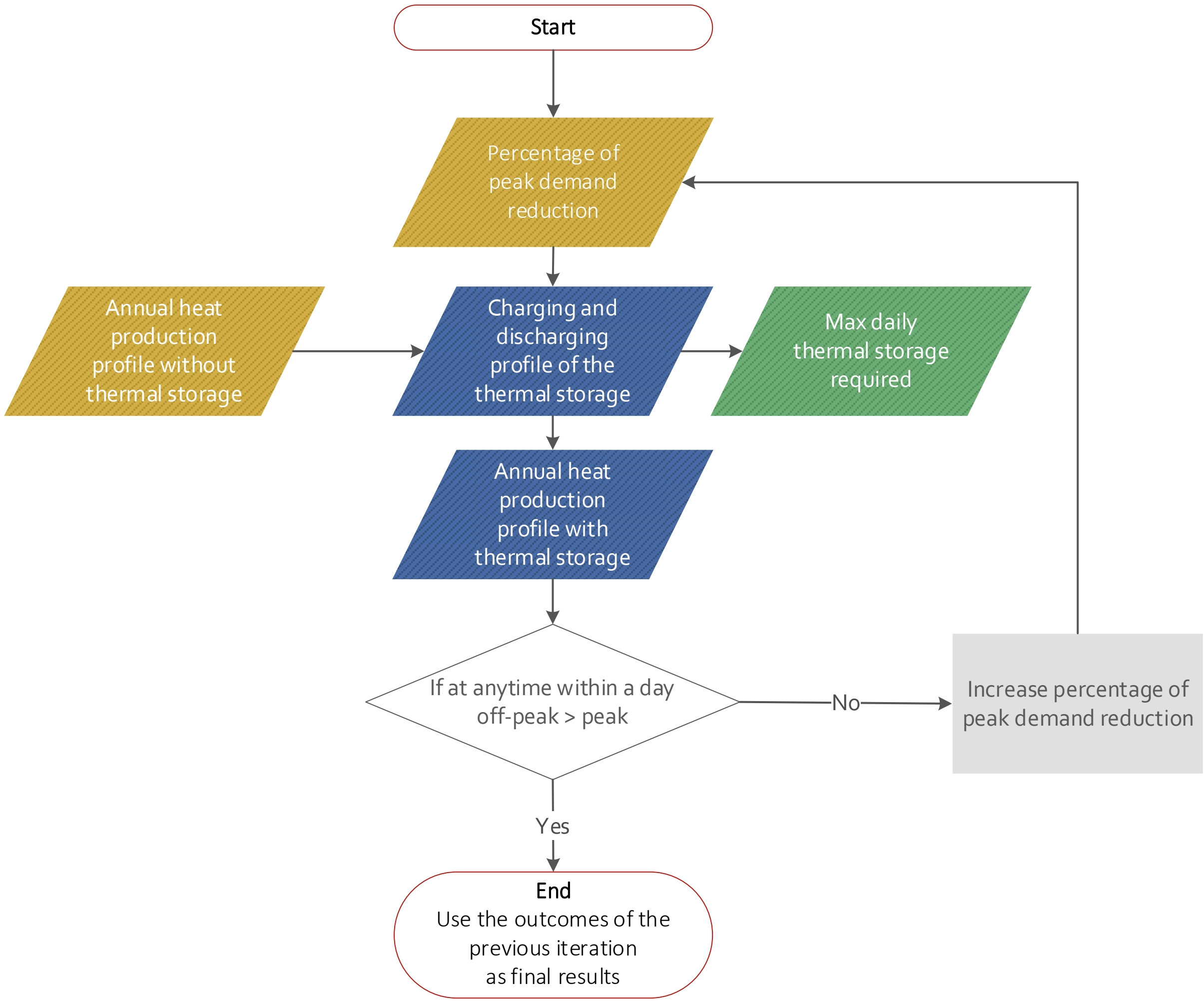


Figure 4-21: The iterative process that was used to calculate the size of the thermal storage and derive the heat production profile of district heating with thermal storage.

4.3.3 Installed Capacity of Heat Supply Technologies in a District Heating Scheme

The capacity of the heat supply technologies installed a district heating scheme was calculated using a combination of screening curves and load duration curve. The screening curves give the relationship between the number of hours of operation of a unit and the annual cost of technologies [70]. The load duration curve illustrates the capacity requirements for heat production.

This methodology was described through the example of a LSOA (code: W01001602) in Newport that was converted to district heating supplied by two heating technologies: an electric boiler and a large-scale GSHP. The domestic heat demand of this LSOA was 16,761 MWh from mainly detached and semi-detached houses.

Figure 4-22(a) shows the screening curves for these two technologies. The electric boiler has a low investment cost but high operating costs, thus they are more economically viable than a geothermal heat pump if their operation time is kept lower than ~1,200 hours/year.

Figure 4-22(b) shows the load duration curve (red line) that was built using the heat production profile produced in Section 4.3.2 considering heat demand in dwellings in the LSOA W01001602. The installed capacity of each technology was calculated using this load duration curve and the screening curve in Figure 4-22(a). This resulted in an installed capacity of 0.7 MW_{th} of electric boilers to cover the peak load and 1.4 MW_{th} of geothermal HPs to supply the baseload.

The installed capacity of each unit did not account for potential cost related to the reinforcement of the electricity network to supply the electricity demand to the electric boilers and geothermal HPs. Considering these costs may result in an increase of the size of the thermal storages.

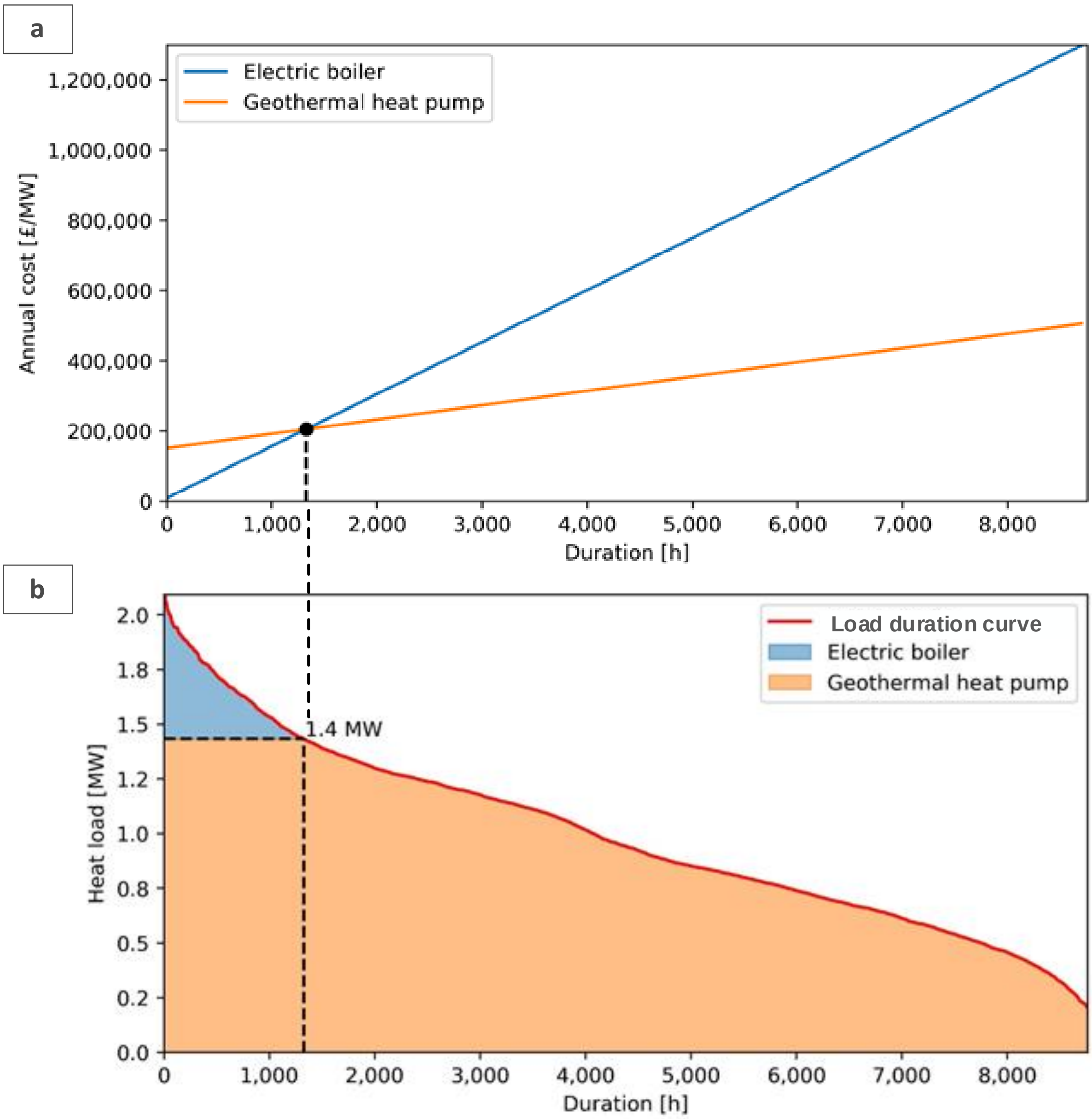


Figure 4-22: Panel a shows the screening curves for two electricity-based units (source of costs from [71]). Panel b shows an example of how the information from the screening curves for electric boiler and geothermal HPs was applied to a load duration curve to calculate the installed capacity of each technology. The load duration curve represents the domestic and non-domestic demand of a LSOA in Swansea.

Figure 4-23 shows the half-hourly heat production of the heat supply units for the LSOA presented in Figure 4-22 over a week. The baseload heat is supplied by geothermal HPs until 1.4 MW, while electric boilers provide the heat to cover the peaks. The peak electricity demand of the district heating system was estimated at 1 MW (0.7 MW from the electric boiler and 0.3 MW from the geothermal heat pump) when considering a COP of 5 for the geothermal heat pump.

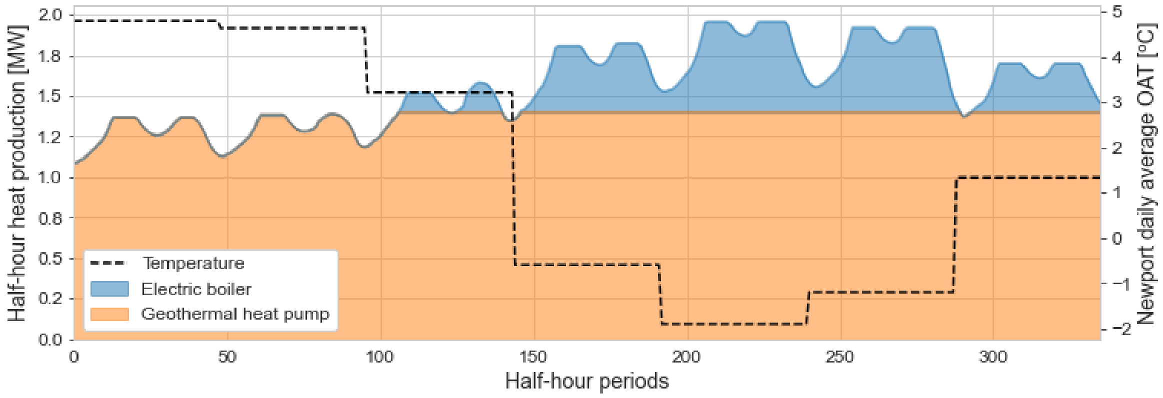


Figure 4-23: An example of the half-hourly heat production of a district heating system with 1.4 MW of geothermal HPs and 0.7 MW of electric boilers for 7 days. The flat tops are due to the use of thermal storage to decrease the peaks.

4.4 Half-hourly Heat Production and Energy Demand for Cardiff, Swansea and Newport

The methods that were developed in Chapter 3 to estimate the annual heat demand and in this chapter to synthesise profiles for ASHPs, GSHPs, resistance heaters, natural gas/hydrogen boilers and district heating were used to produce half-hourly heat production and energy demand for two heat decarbonisation pathways for 2050 for the case studies in Cardiff, Swansea and Newport.

The following two heat decarbonisation pathways were studied:

1. The electrification pathway, where 100% of the domestic heat was supplied by electricity; and,
2. The hydrogen pathway, where the natural gas network was converted to a hydrogen network and the rest of the heat was supplied through HPs.

The carbon intensity of electricity and hydrogen were predicted to be 0 g_{CO2e}/kWh by 2050. This is a prerequisite for the heating sector to be aligned with the carbon target set by the UK government. In addition to the year 2050, the years modelled were the baseline year 2018 and the intermediate years 2030 and 2040.

Figure 4-24 shows the methodology that was used to produce the heat production and energy demand profiles. It entailed three steps:

1. Estimating annual heat demand for each LSOA considering the number and types of dwellings and their energy efficiencies (see Chapter 3);

2. Correcting the annual heat demand based on the daily average OAT profile of the target year (see appendix C.1); and,
3. Synthesising half-hourly heat production and energy demand for each LSOA based on the heat supply mix of the two decarbonisation pathways.

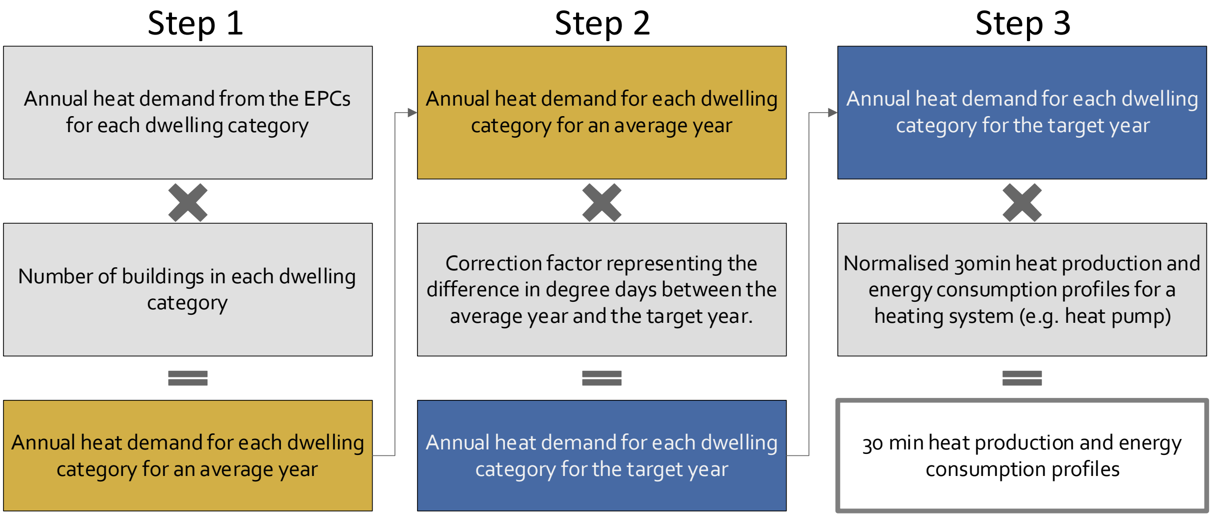


Figure 4-24: Three-step approach for producing half-hourly heat production and energy demand profiles. The average year corresponds to the temperature profile used to produce EPCs (see Section 3).

4.4.1 Assumptions for the Electrification and Hydrogen Pathways

The heat supply mix and heat demand of the two decarbonisation pathways were decided based on the local characteristics of the dwelling stock in 2018, which included the heating technologies installed, the heat density, the potential heat savings from energy efficiency measures, the number of dwellings connected to the gas grid and the number of new dwellings by LSOA.

The number of heating technologies installed and the annual heat demand by LSOA in 2018 was shown in Chapter 3. The heat density was then calculated by dividing the annual heat demand by the area of the LSOA.

The number of dwellings connected to the gas grid at LSOA level in 2011 was calculated from the number of domestic gas meters published by BEIS [72] and distributed across the different type of dwellings based on the following assumptions:

1. All dwellings using gas boilers were connected to the gas grid,
2. Dwellings using biomass/oil were not connected to the gas grid,
3. The unallocated gas meters after step 1 and 2 were distributed across the dwelling using resistance heaters.

The share of dwellings connected to the gas grid was kept constant when projecting the numbers of dwellings to 2018. Figure 4-25 shows the share of gas connected dwellings in each LSOA in the three local authorities in 2018. The LSOAs with a low share of gas boilers are the LSOAs with fewer dwellings connected to the gas grid. Oil and biomass boilers usually are used where there is no gas connection.

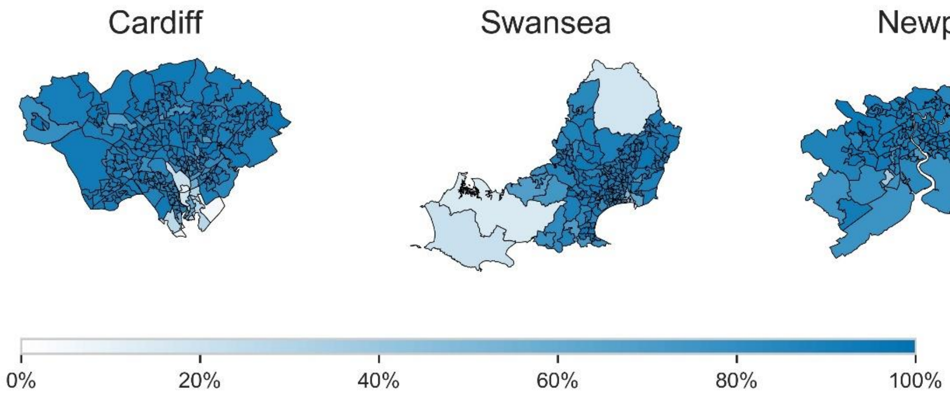


Figure 4-25: Maps of Cardiff, Swansea and Newport showing the share of gas connected dwellings in 2018 at LSOA level

The heat demand from new dwellings was estimated in three steps:

1. The local development plan (LDP) areas for new dwellings available on the local authorities' websites were mapped with the LSOAs. Using GIS software, the LDP sites for each local authority were overlaid on a LSOA map. LSOAs falling into these sites were identified.
2. The projected number of new dwellings shown in Figure 4-26 were distributed to the identified LSOAs.
3. The heat demand associated with these new dwellings was calculated. The CCC suggested a target of 15-20 kWh/m^2/year for space heating in new dwellings to meet the net-zero target [73]. In this report, the value of 17.5kWh/m^2/year was multiplied by the average floor area of the dwellings of each local authority and the number of new buildings in each LSOA to calculate the additional heat demand. For hot water demand, an average annual energy demand per dwelling of 1,570 kWh was used [74].

Figure 4-26 shows the projection for the number of dwellings in 2030, 2040 and 2050 for the three local authorities. By 2050, there were 22,732 new dwellings expected to be built in Cardiff compared to 2018, 17,072 in Swansea and 14,026 in Newport.

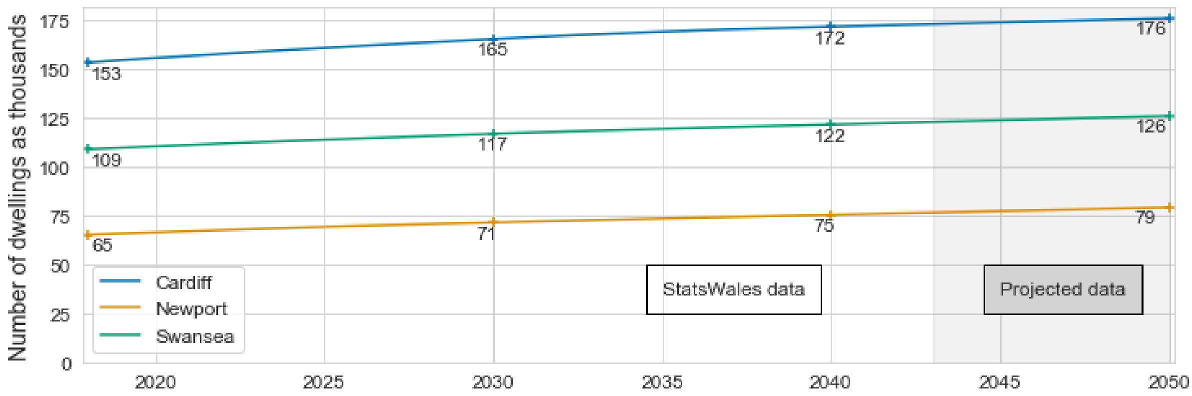


Figure 4-26: Numbers of dwellings from 2018 to 2050. Figures from 2018 to 2043 were extracted from StatsWales [54], a linear extrapolation using data from 2038 to 2043 was used to project these figures to 2050.

This information was used with the following assumptions to create the two decarbonisation pathways. The common assumptions to the two pathways entailed that:

- All existing dwellings reach their potential EPC rating by 2050, which happens linearly.
- All existing dwellings not connected to the gas grid have HPs installed. Linear interpolation was used for the uptake of HPs in dwellings using resistance heaters, while all oil boilers and biomass boilers will be replaced by HPs by 2030.
- The new dwellings built between 2018 and 2030 have HPs installed or are converted with HPs by 2030. After 2030, all new dwellings have HPs installed. No new dwelling is connected to the gas grid.
- For existing and new dwellings, HPs are installed in the ratio 7/8 ASHPs and 1/8 GSHPs in detached and semi-detached houses. In existing terraced and flats dwellings, only ASHPs are installed.

Table 4-3 describes the assumptions that are specific to each decarbonisation pathway for the existing dwellings.

Table 4-3: Additional assumptions for existing dwellings that were used to model the electrification and hydrogen pathways.

Electrification pathway	Hydrogen pathway
• 80% of the existing dwellings in LSOAs with heat density above 30 kWh/m2 are connected to district heating by 2030. • District heating supply mix includes electric boilers and geothermal HPs. In Cardiff, energy from waste CHP units is also part of the heat supply mix. For the geothermal HPs, an average annual COP of ~5 was considered, as suggested by [75]. • The remaining gas boilers and resistance heaters are linearly replaced by HPs from 2018 to 2050, consequently the share of HPs reaches 100% by 2050.	• All existing dwellings connected to the gas grid are converted to hydrogen boilers by 2050, with the following conversion rate: 0% in 2030, 50% in 2040 and 100% in 2050.

The half-hourly profiles for 2030, 2040 and 2050 were produced using the temperature profiles shown in Figure 4-27 as inputs to the models from Section 4.2 for the two decarbonisation pathways. These daily average OAT profiles were chosen because they represented a “typical” year in terms of days close to the daily average wind and OAT of the past 40 years.

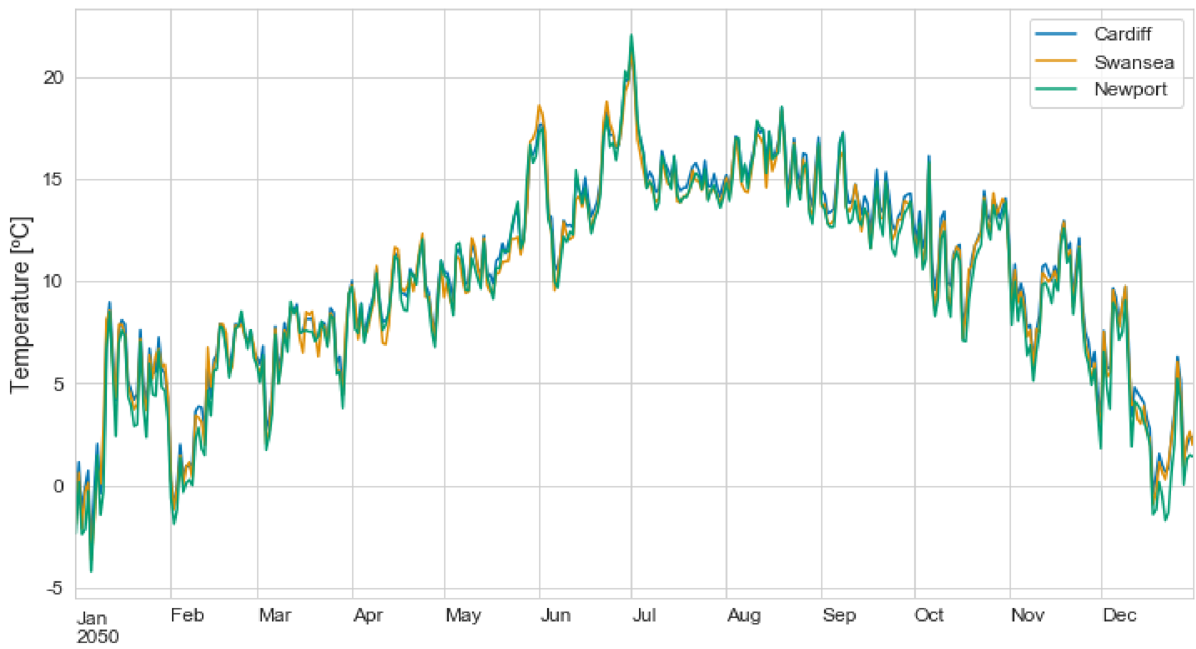


Figure 4-27: Typical daily average OAT profiles for Cardiff, Swansea and Newport (corresponding to the year 2009).

4.4.2 Results

This section will describe the results obtained for the two pathways, including the changes in the annual heat demand, the heat supply mixes, the half-hourly heat production and half-hourly energy demand for the three local authorities.

Figure 4-28 shows the change in the annual heat demand between 2018 and 2050. Across the three local authorities, the heat demand decreases by 28 to 30% between 2018 to 2050. This is due to the impact of energy efficiency measures on the existing stock and the low heat demand of the new dwellings. The heat produced in the hydrogen pathway is equal to the heat demand. However, there is a mismatch in the electrification pathway because of the district heating. To compare the two pathways, this section will focus on heat production.

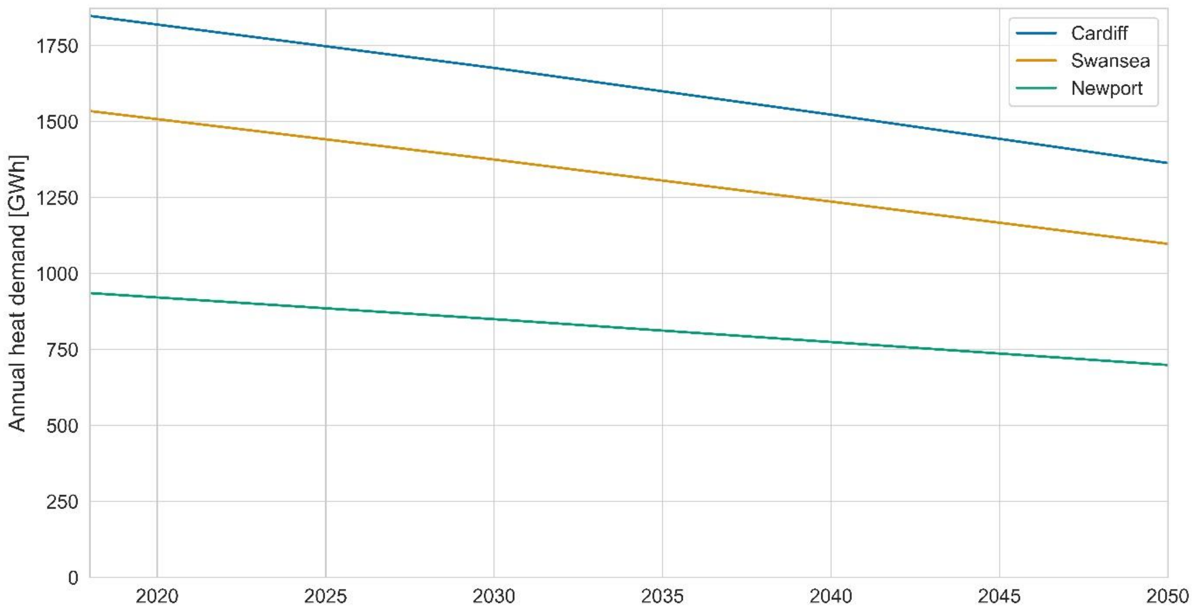


Figure 4-28: Annual heat demand for Cardiff, Swansea and Newport between 2018 and 2050, excluding district heating losses. The lines were built by linearly interpolating data between the years 2018, 2030, 2040 and 2050.

Figure 4-29 shows the share of the annual heat produced by each technology in 2018, 2030, 2040 and 2050 in the electrification pathway. In 2018, based on the heat demand data production in Section 3,more than 93% of the heat was supplied by gas boilers across the three local authorities. By 2030, the share of district heating reaches its maximum in 2030 with 15 to 26% of the heat supplied, whereas the uptake of HPs continues until it reaches 70 to 86% of the heat supplied in 2050. Overall, all of the changes resulted in a share of heat supplied by gas boilers of 40-45% in 2030, 20% in 2040 and 0% in 2050. More details regarding heat supply units for the district heating scheme are available in Appendix E.1.

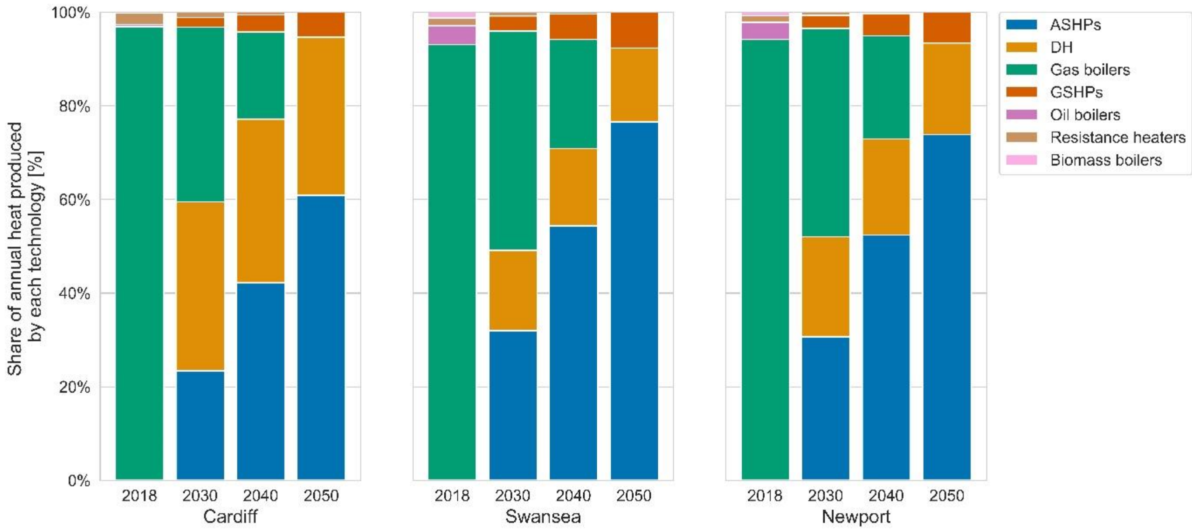


Figure 4-29: Share of heat produced by each technology in Cardiff, Swansea and Newport in 2018, 2030, 2040 and 2050 for the electrification pathway.

Figure 4-30 shows the share of the annual heat produced by each technology in 2018, 2030, 2040 and 2050 in the hydrogen pathway. No significant change happens before 2040 in the hydrogen pathway because it is not expected to see a large share of the gas grid converted to hydrogen before this date. Hence, the share of heat supplied by gas boilers remains above 92% across the three local authorities. From 2040, it drops below 47%. By 2050, 92 to 95% of the heat is supplied by hydrogen boilers. HPs supply 5 to 7% of the heat by 2050.

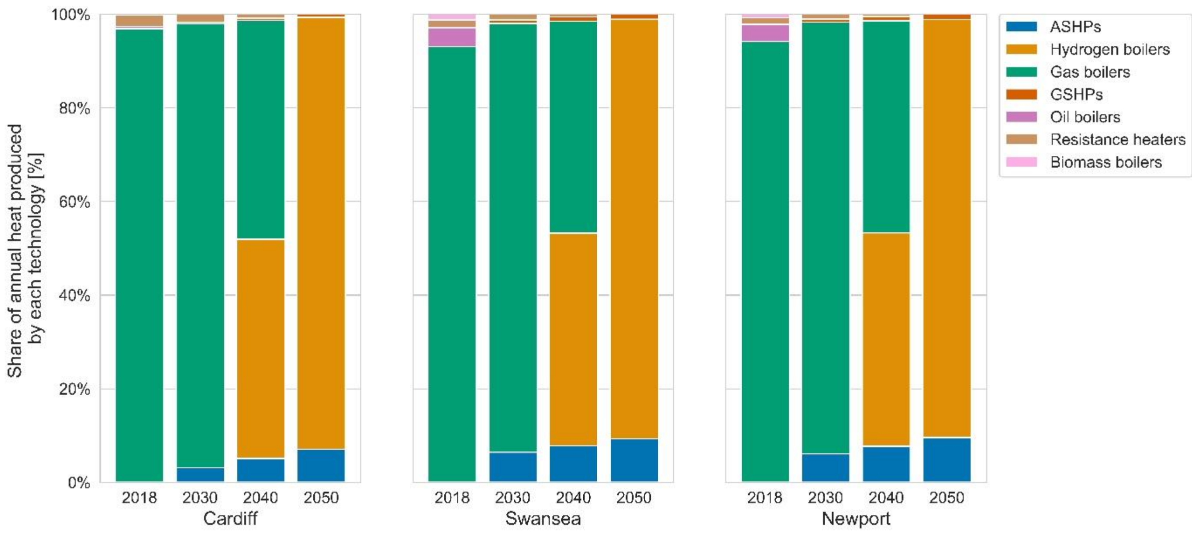


Figure 4-30: Share of heat produced by each technology in Cardiff, Swansea and Newport in 2018, 2030, 2040 and 2050 for the hydrogen pathway.

Figure 4-31 shows the aggregated heat production profile of each local authority for 2050 for the two pathways. Similar annual heat production across the three local authorities is observed, with 2-5% higher heat production for the electrification pathways because of the district heating losses. The heat production peaks are at least 1.6 higher in the hydrogen pathway than the electrification pathway. For instance, the heat production peak reaches 427 MW in the electrification pathway and 722 MW in the hydrogen pathway in Cardiff. Similar observations are made in Swansea and Newport. This is due to the difference in the way in which heat is dispatched by the different heat supply technologies. The profiles for the years 2030 and 2040 can be found in Appendix E.2.

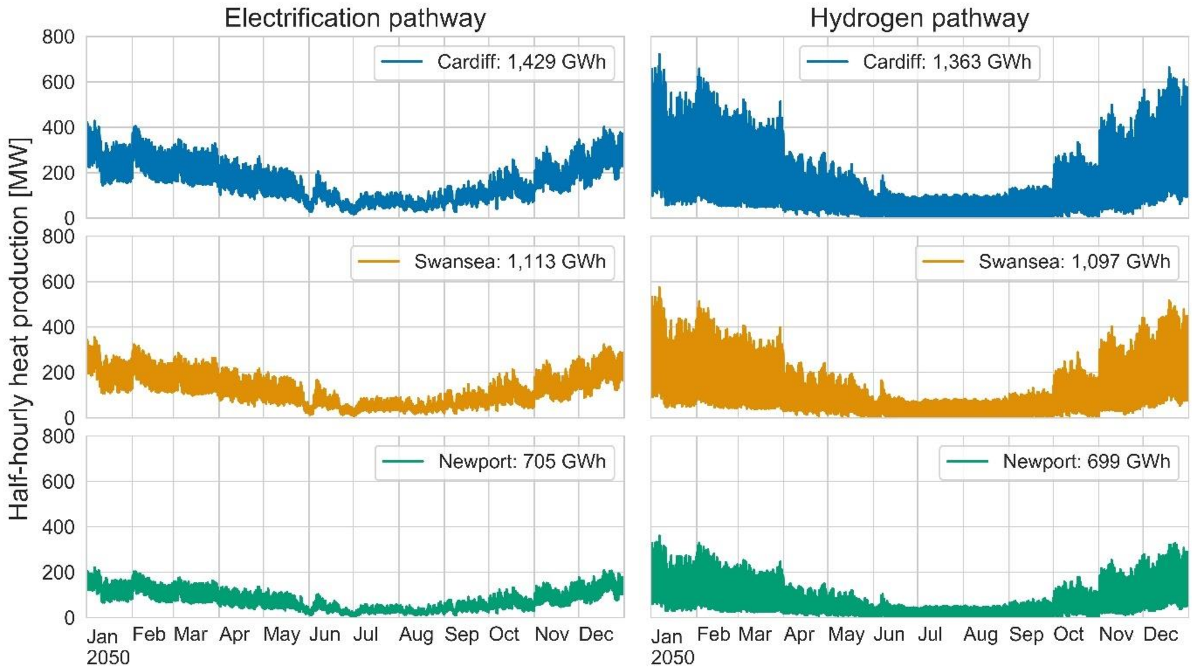


Figure 4-31: Aggregated half-hourly heat production profiles of Cardiff, Swansea and Newport in 2050 for the electrification and hydrogen pathways. The values in the legend are the annual heat demand.

Figure 4-32 shows the aggregated electricity for heat demand profile of each local authority for 2050 for the two pathways. The electricity demand, as well as the electricity peak, are around ten times higher in the electrification pathway than in the hydrogen pathway. In Cardiff, the peak reaches 164 MW in the electrification pathway and 16 MW in the hydrogen pathway. In 2018, the peak is 15 MW for Cardiff. In the electrification pathway, the electricity for heat in Cardiff and Swansea was similar, despite heat production being higher for Cardiff. This is explained by the combination of a higher share of district heating in Cardiff and the higher efficiency of large-scale HPs when compared to individual HPs.

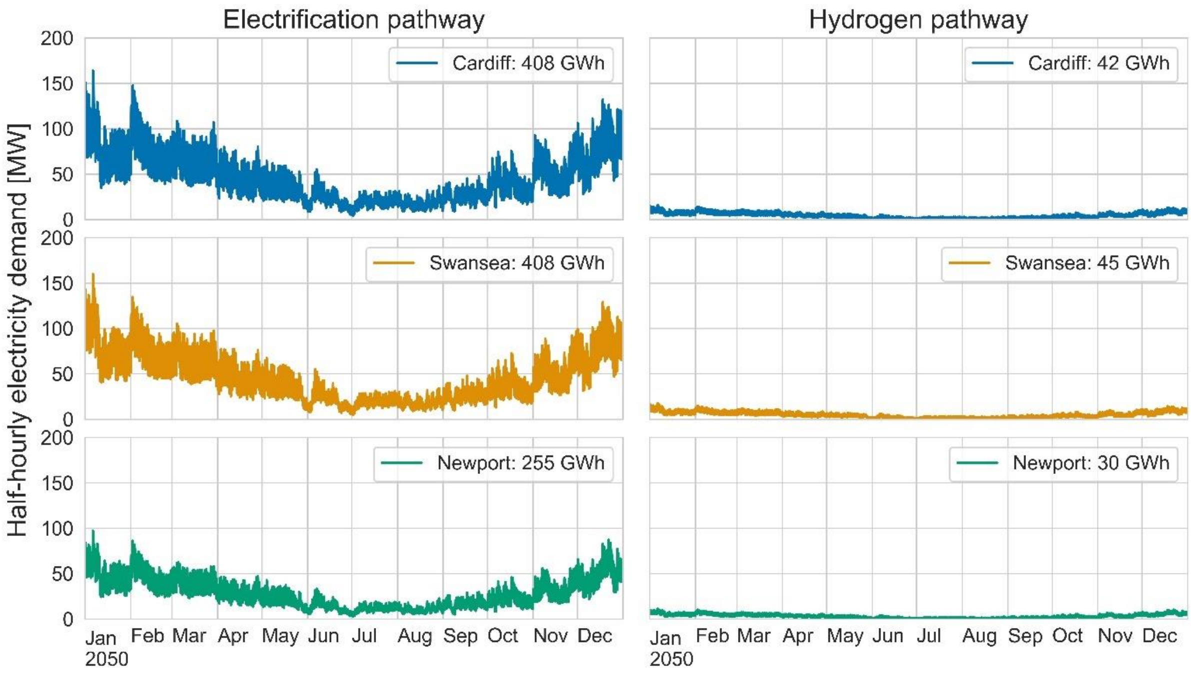


Figure 4-32: Aggregated half-hourly electricity for heat demand profiles of Cardiff, Swansea and Newport in 2050 for the electrification and hydrogen pathways.

Figure 4-33 shows the aggregated hydrogen for heat demand profile of each local authority for 2050 for the hydrogen pathway. The profiles are very similar to the heat production profiles shown in Figure 4-31. The peaks are slightly higher because the efficiency of hydrogen boilers is 84%.

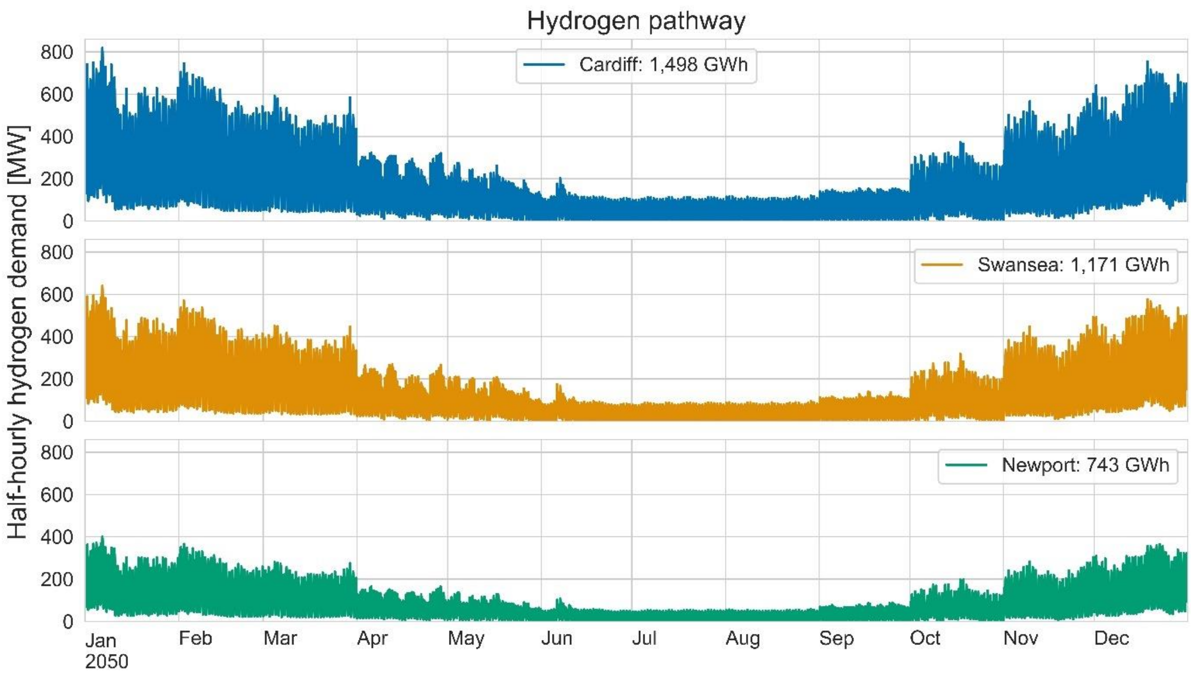


Figure 4-33: Aggregated half-hourly hydrogen for heat demand profiles of Cardiff, Swansea and Newport in 2050 for the hydrogen pathway.

Table 4-4 summarises the characteristics of the state of the system in 2018.

Table 4-5 and Table 4-6 summarise the characteristics of the electrification and hydrogen pathways in 2050 by showing the annual amount of energy and the peak associated with each energy vector. This shows that the amount of secondary energy[7] use is three times higher in the hydrogen pathway than in the electrification pathway. This is due to the average annual efficiency of HPs, which is above 250%.

Table 4-4: Summary of the characteristics of the heat production and electricity demand for heating in 2018 by local authorities (LAs).

LA	Cardiff		Swansea		Newport	
Energy vector	Heat	Electricity	Heat	Electricity	Heat	Electricity
Annual energy [GWh]	1,847	45	1,534	23	935	5
Peak [MW]	427	15	354	8	220	13

Table 4-5: Summary of the characteristics of the electrification pathway in 2050 by local authorities (LAs) including heat production and electricity demand for heating with losses.

LA	Cardiff		Swansea		Newport	
Energy vector	Heat	Electricity	Heat	Electricity	Heat	Electricity
Annual energy [GWh]	1,429	408	1,113	408	705	255
Peak [MW]	427	164	354	160	220	97

[7] Secondary energy includes resources that have been converted or stored and cannot be directly harnessed in nature. In this study, it includes electricity and hydrogen.

Table 4-6: Summary of the characteristics of the hydrogen pathway in 2050 by local authorities (LAs) including heat production, electricity demand for heating and hydrogen demand for heating with losses.

LA	Cardiff			Swansea			Newport		
Energy vector	Heat	Electricity	H2	Heat	Electricity	H2	Heat	Electricity	H2
Annual energy [GWh]	1,363	42	1,498	1,097	45	1,171	699	30	743
Peak [MW]	722	16	819	574	18	639	360	11	400

4.5 SUMMARY

In this chapter, models were created for different individual heating technologies. These models were shown to have good accuracies when representing the shape of the heat and energy demand profiles, including the total energy and the peaks. Furthermore, a method to synthesise heat and energy demand profiles for district heating that accounts for losses and thermal storage was also described. Table 4-7 shows a summary of the accuracy of the models for ASHPs, GSHPs, resistance heaters and gas boilers when compared to the training data during a cross-validation procedure.

Table 4-7: Summary of the performances of the models created when performing a cross-validation procedure

Accuracy [%]	ASHPs	GSHPs	Resistance heaters	Gas boilers
Total heat production	1%	1%	0%	1%
Total energy demand	1%	0%	0%	1%
Peak of heat production	-9%	-6%	-11%	-1%
Peak of energy demand	-5%	-5%	-11%	-1%

However, there are limitations to these models. The datasets from trial projects used to train the machine learning models for each technology may not provide a good representation of how the heating technologies are controlled or of the behaviour of people regarding heating. This is particularly true for the ASHPs and GSHPs datasets which are based on a relatively small samples of only social housing dwellings (<700 in total). Furthermore, a better parametrisation of the models or other type of model (e.g., artificial neural networks, support vector machines, etc.) may provide better accuracy when representing the peaks in the profiles compared to the current models.The models for the individual heating technologies and the method to synthesise half-hourly profiles for district heating were applied to case studies of Cardiff, Swansea, and Newport using two decarbonisation pathways. The results emphasized how the use of different heat technologies in the two decarbonisation pathways impacted the peak of the heat production, while the annual heat demand remained similar. The secondary energy demand for heat was also observed to be impacted by the choice of the heating technologies, due to the differences in the efficiency of ASHPs/district heating generation technologies compared to hydrogen boilers.

In summary, the key points from the results are:

- The peak of the heat production was more than 1.6 times higher in the hydrogen pathway than in the electrification pathway.
- The secondary energy demand for heat was three times higher in the hydrogen pathway than in the electrification pathway.
- The peak electricity for heat demand increased by a factor of ten in the electrification pathway. This was for a typical year in terms of temperature and further studies will be done in Chapter 5 to show the potential challenges ahead.

5 Estimating the Peak Electricity Demand for Heating

5.1 Introduction

HPs are expected to play an important role in both the electrification and hydrogen pathways, as described in Chapter 4. This potentially requires the electricity distribution network to be reinforced to sustain the additional load created by HPs.

To assess the level of reinforcement, the maximum electricity required to fulfil heat demand for a half-hour period for the highest demand day will be calculated, which is referred to as the 1-in-20[8] peak electricity demand. Two methods will be described to calculate this figure. The first method calculates the 1-in-20 peak electricity demand for a specific daily average outside air temperature (OAT). This method is then applied to study the peak electricity demand of individual heating technologies, as well as the total peak electricity demand for the two heat decarbonisation pathways. The second method expands on the first method to calculate the After Diversity Maximum Demand (ADMD) of a heating technology for different daily average OAT. It is used to calculate the ADMD of ASHPs for OATs of -5°C to +5°C and the additional peak electricity demand created by their uptake in the electrification pathway.

The ADMD is the ratio between the coincident maximum load of a system and the number of units N in the system, as shown in Equation 7. It is also defined as the total connected load in the system divided by the number of units in the system, and the diversity factor D.

$$ADMD = \frac{Coincident\ maximum\ load}{N} = \frac{Total\ connected\ load}{N \times D} \tag{7}$$

The ADMD for the design of a low voltage distribution network supplying dwellings is currently calculated based on values for different technologies published by the DNOs which accounts for factors such as dwelling types, EPC ratings, heating systems and electric vehicles [76]. For electricity-based heating systems, the ADMD is equal to the installed capacity of these systems. This conservative approach is to size distribution

[8] The demand that is estimated to happen once every 20 years.

networks for worst case scenarios. However, applying this approach to medium or high voltage distribution network may result in oversizing.

The system that is considered in this chapter are populations of the same heating technologies.

5.2 METHODOLOGY

The two methods described in Chapter 4 were used to synthesise the profile for the highest demand day to calculate the ADMD of heating technologies.

The models from Chapter 4 were trained on aggregated half-hourly heat production and demand of pools of units, such as those profiles embedded in the diversity factor of gas boilers, resistance heaters, ASHPs and GSHPs. This was also the case for the synthesised profiles produced with these models, which enabled them to estimate the aggregate peak electricity demand and the ADMD of the different heating technologies.

5.2.1 Estimation of the 1-in-20 Peak Electricity Demand

The 1-in-20 peak electricity demand method was borrowed from the gas sector. For the gas sector, this represents the daily gas demand that has a probability of occurring once every 20 years [77]. In this study, this represents the half-hourly electricity demand. This happens at a specific time (e.g., day of the week, month, season, etc.) and in specific weather conditions (e.g., OAT, wind, irradiance, etc.).

For simplification purposes, only time related aspects and OATs were used to estimate the highest half-hourly electricity demand for heating the power system in this study. This included the following steps:

1. Identifying the daily OAT producing the highest daily gas demand in the past 20 years in the geographical area studied. In South Wales, the value was provided by Wales and West Utilities (the gas network operator of South Wales) and was -4.2°C.
2. Using -4.2°C as the average daily OAT for a week in winter that did not include any specific dates (e.g., holidays, bank holidays, etc.) to synthesise the electricity demand of the heating technologies: ASHPs, GSHPs, resistance heaters, district heating units. From one day to another, the demand can change due to the behaviours of the users. For instance, it was observed that the demand on a Monday is often different from the demand on a Wednesday or a Friday in the trial data.

3. Aggregating the results and extracting the day that includes the highest half-hourly electricity demand (i.e., the 1-in-20 peak electricity demand).

5.2.2 Calculation of the ADMD of Individual Technologies

The literature (e.g. [45], [76]) includes values of the ADMD for different heating technologies, which can be used to calculate the additional peak electricity demand that is produced when installing new units. However, these values are not given for a specific OAT, which is a barrier in their use in other studies. For heating technologies such as ASHPs, the ADMD changes with the COP and the heat demand. To solve this problem, a method was developed in this study to produce values of the ADMD against OAT for a heating technology with a given rated capacity.

The peak electricity demand P produced by a population of N heating units was calculated using the $ADMD$ of the heating technology. Its coincidence factor CF is shown by Equation 8. CF is defined as the fraction of the peak demand of a population in operation at the time of the system peak [2] (e.g., the fraction of the peak demand of ASHPs at the time of the peak of the GB power system). The CF of local system may get a different value to the CF of the GB system as the share of the different type of loads connected at local level may not be similar to the shares seen in the GB system.

$$P = N \times ADMD \times CF \tag{8}$$

Note that this equation does not apply when the N units create a new system peak at another time of the day than the current system peak.

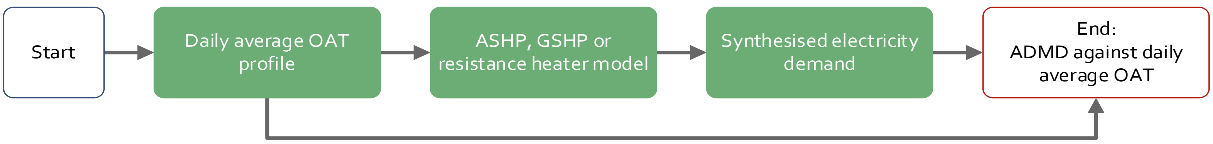


Figure 5-1: Method to estimate the values of the ADMD against temperature for a heating technology.

Figure 5-1 shows how the synthesised half-hourly electricity demand using the models for ASHP, GSHP or resistance heaters from Chapter 4 are combined with the annual heat demand from Chapter 3 to extract the values of the ADMD for different temperature steps.

It entailed three main steps:

1. Using a daily average OAT profile with a range of values that includes the 1-in-20 OAT (-4.2°C in the case of South Wales).
2. Synthesising the electricity demand profiles for the heating technology using the model from Chapter 4 and scaling it based on the annual heat demand from Chapter 3.
3. Calculating the values of the ADMD for different daily average OATs.

These steps used several daily average OAT profiles and the results are aggregated.

5.3 The Peak Electricity Demand for Individual Heating Technologies

The heat production and energy demand profiles (after diversity) of an ASHP, a GSHP, a resistance heater and a natural gas/hydrogen boiler were synthesised using Method 5.2.1 for an average winter day (OAT of 5.8°C) and a 1-in-20 peak demand day with an OAT of -4.2°C. Although natural gas/hydrogen boilers do not use electricity as their main energy input, they were included for comparison purposes.

Figure 5-2 shows the half-hourly heat production of the four heating technologies. All of the technologies supplied 50 kWh of heat over the average winter day and 85 kWh over the 1-in-20 peak demand day. The differences in the profiles may be explained by the technical characteristics of the heating technologies, as well as the impacts of time of use electricity prices.

The natural gas/hydrogen boiler has a higher thermal output compared to the other technologies and can therefore provide sufficient heat in a short period to meet the comfort temperature. This is reflected in the blue line showing a bimodal pattern with a large difference between the minimum and the maximum heat output.

Electricity-based technologies commonly have a lower thermal output than natural gas/hydrogen boilers, which requires them to work at a more constant load to avoid the inside air temperature dropping too low in the dwelling. It is also observed that:

- To take advantage of the low electricity prices (e.g., electricity tariff with off-peak and on-peak prices), resistance heaters are often combined with hot water tanks for domestic hot water demand. This enables them to reach their maximum production during the night/off-peak period to store the excess heat, which is then released during on-peak times.

- The maximum heat production by the ASHP and the GSHP occurs in the morning (slightly higher than their heat production in the evening) because this is when the OAT is usually the lowest, while the difference between the comfort temperature and the inside air temperature is the highest.

When comparing the profiles of an average winter day with a 1-in-20 peak demand day, the daily heat production of the heating units was increased by a factor of 1.7 to cover the additional heat losses with the drop of the outside air temperature. Peak heat production increases by the same factor (1.7) as the heat production for GSHP, by a factor of around 1.5 for ASHP and gas boiler and by 2 for a resistance heater. The higher increase for the resistance heater may be explained because hot water tanks are not large enough to support the heat demand for a 1-in-20 peak demand day. This requires an increase in the heat production of the resistance heaters to supply the afternoon/evening peak heat demand.

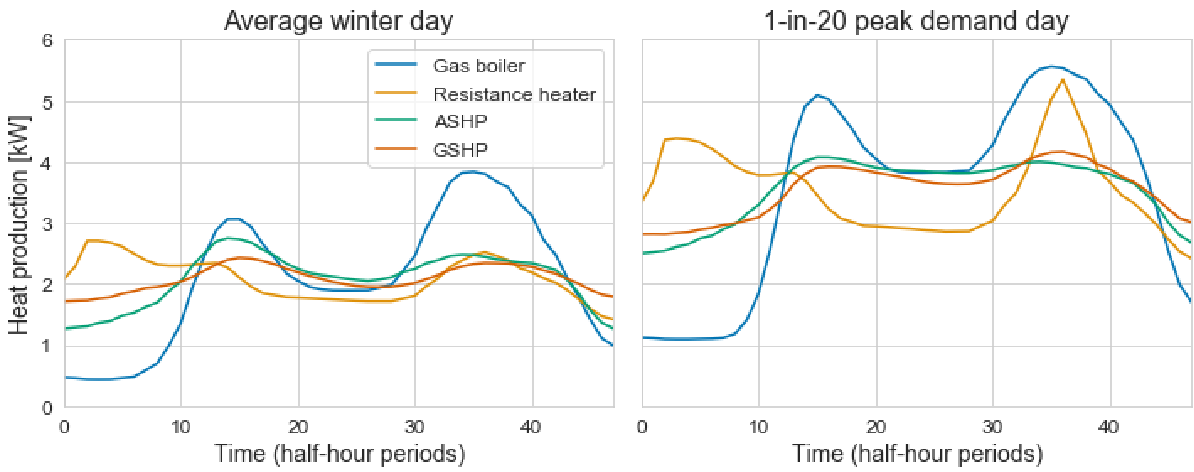


Figure 5-2: Half-hourly heat production profiles of different heat technologies produced using the models developed in Chapter 4 for Cardiff for an average winter day (T=5.8°C) and the 1-in-20 peak demand day (T=-4.2C°). Heat production on the average winter day for each technology was fixed at 50 kWh. The heat production for the 1-in-20 peak demand day was increased by a factor of 1.7 compared to the heat produced for an average winter day to reflect the increase of the heat losses. Gas boilers include natural gas and hydrogen boilers.

Figure 5-3 shows the half-hourly energy demand of the four technologies for an average winter day and the 1-in-20 peak demand day based on the heat production from Figure 5-2.

The peak electricity demand of the ASHP for a 1-in-20 peak demand day is twice as high as that for an average winter day. This is more than the increase in heat production (1.7) and can be explained by the decrease in the COP of the ASHP, which caused by the decrease of the OAT. The increase is slightly lower (i.e., 1.9) for GHSPs because the COP of GSHPs is not as sensitive to OAT that of ASHPs.

For the gas boiler and the resistance heater, the efficiency remains the same regardless of the OAT. Thus, a factor of 1.7 is observed between the peak energy demand of an average winter day and a 1-in-20 peak demand day.

Overall, for the same amount of heat produced on a 1-in-20 peak demand day, the peak in energy demand can vary by a factor larger than 3 across the four technologies. A factor of 3.2 was observed between the ASHP electricity demand peak and the natural gas/hydrogen boiler peak. Similar ratios were observed for the daily energy demand with 33 kWh for GSHP, 42 kWh for ASHP, 85 kWh for resistance heater and 101 kWh for natural gas/hydrogen boiler.

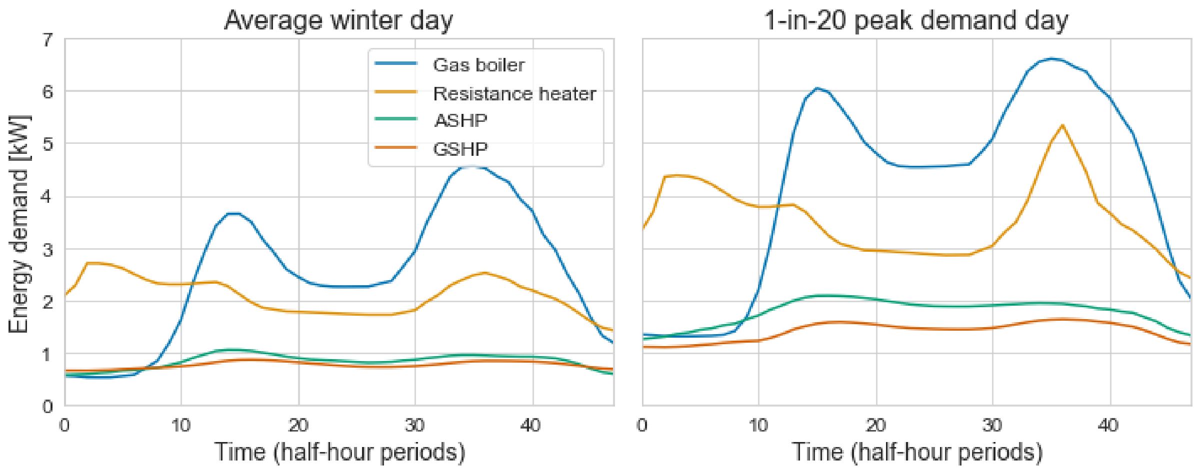


Figure 5-3: Energy demand of different technologies for an average winter day in Cardiff and for a 1-in-20 peak demand day to supply the heat shown in Figure 5-2. The gas boiler includes natural gas and hydrogen boilers.

Figure 5-4 shows the average half-hourly electricity demand of a weekend day and a weekday for winter 2018 in the UK. It also shows the peak demand day, which fell on the 1st of March. The UK peak electricity demand happens in the afternoon between around 5 and 6 pm for the average weekday and weekend day. Using this information, the coincidence factor of the heating technologies was calculated, the results follow.

Resistance heaters peak in the afternoon at the same time as the GB electricity peak—thus they had a coincidence factor of 1.

For ASHPs, the peak electricity demand was in the morning. The afternoon electricity demand of the ASHPs, which coincided with the national peak, was around 90% of the morning peak—or a coincidence factor of 0.9.

For GSHPs, the peak electricity demand happened in the afternoon at the same time as the national peak—thus the coincidence factor was 1.

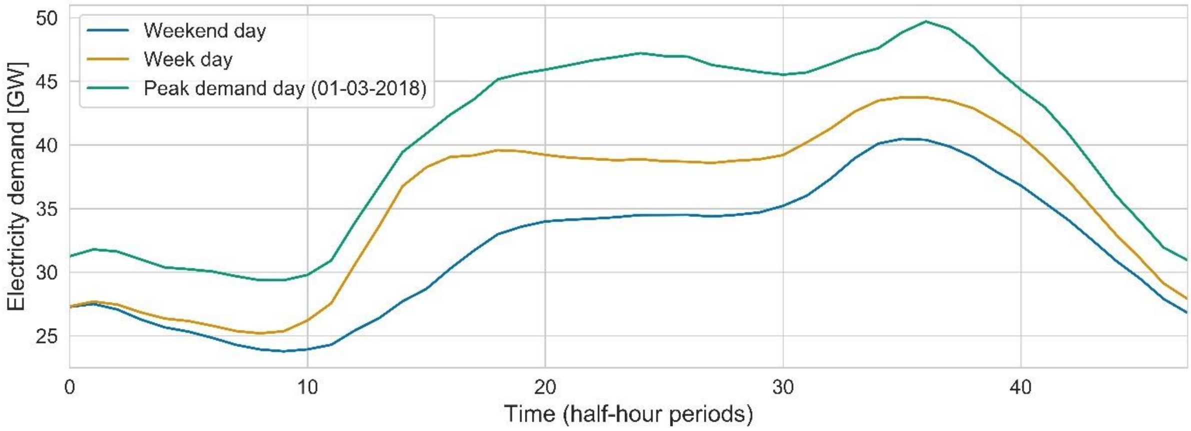


Figure 5-4: Average GB electricity demand profiles in winter (1st of November to 31st of March) *produced using 2018 electricity demand data, "ND" column [78].*

5.4 CALCULATING THE ADMD OF ASHPS

In the two decarbonisation pathways, ASHPs were seen to play a major role in heat decarbonisation. Their ADMD was calculated and used to estimate the additional peak electricity demand that could be created by the uptake of this technology in Cardiff, Swansea and Newport based on the assumptions from the electrification pathway using the method given in Section 5.2.2.

The ADMD of the ASHPs was calculated for three dwelling types: detached, semi-detached and terraced. For each dwelling type, 60 daily average OAT profiles were used as input data. The 60 daily average OAT profiles were derived from five UK historical annual daily average OATs, going from 2013 to 2018. For each UK historical annual profile, the daily average OAT was shifted by either 0°C, ±1°C, ±2°C, … and ±6°C to create 12 new profiles each time. The average annual heat demand was estimated using the EPC-based method (Chapter 3) for detached, semi-detached and terraced houses in Cardiff, Swansea and Newport.

Figure 5-5 shows the ADMD of the ASHPs for average detached, semi-detached and terraced houses. The ADMD of the ASHPs for the three dwelling types increase as OAT decreases. Detached dwellings are on average larger than semi-detached and terraced dwellings. This is reflected by the ADMD of detached dwellings being the largest.

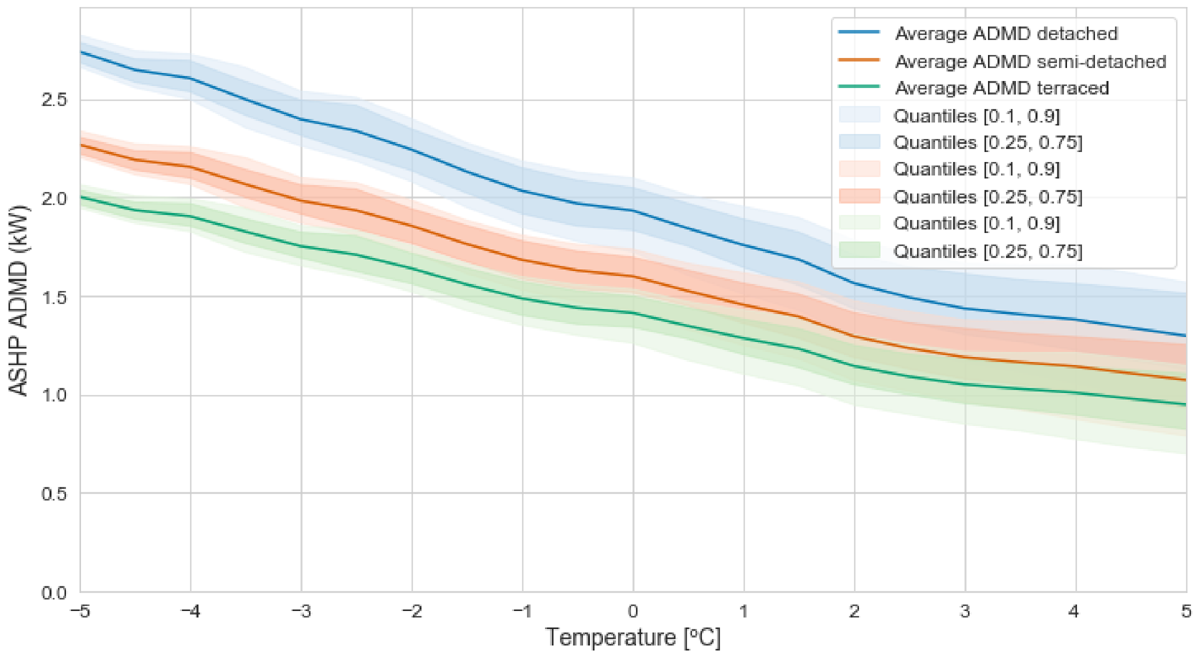


Figure 5-5: Average ADMD of a pool of ASHPs against outside air temperature for detached, semi-detached and terraced houses based in Cardiff, Swansea and Newport.

The diversity factor of the ASHPs was calculated using the values of the ADMD of ASHPs shown in Figure 5-5 with the thermal output required to heat an average detached, semi-detached and terraced house (see Appendix C.2), which was compared to two other sources. The first source was the Customer-Led Network Revolution project that was led by Northern Powergrid in 2014, which produced Equation 9 [79]. This links N, the number of ASHPs with a rated capacity of 4.18 kW, to the ADMD. By using $N = 100$, the diversity factor was calculated to be 3.4. However, Northern Powergrid do not specify the temperature of the electricity demand data that this equation is based on.

$$ADMD_{ASHP} = 3.012998 \times N^{-0.195356} \quad (9)$$

The second source was drawn from the framework to design low voltage networks[9] produced by DNOs in GB. It shows that DNOs have a conservative approach for ASHPS and consider no diversity (i.e., D$iversity\ factor = 1$).

Figure 5-6 shows the diversity factors against OAT from this study and the two sources. The diversity factor from this study decreases with the OAT. This can be explained by the increase of the heat load supplied by the ASHPs with lower OAT combined with a

[9] An example of a design document from the Scottish Power Energy Networks can be found at [12]

decrease in their COP. Using only the original trial dataset, the diversity factor would be found in the interval (4, 5.8) at 0°C. The authors from [45] found an ADMD of 1.7 for ASHPs using the same trial datasets, which is equivalent. Using the modelled data, the diversity factor falls in the interval (2.9, 4.1) at the OAT of the 1-in-20 peak demand day (-4.2°C). The diversity factor from the Customer-Led Network Revolution project (3.4) is also in this interval.

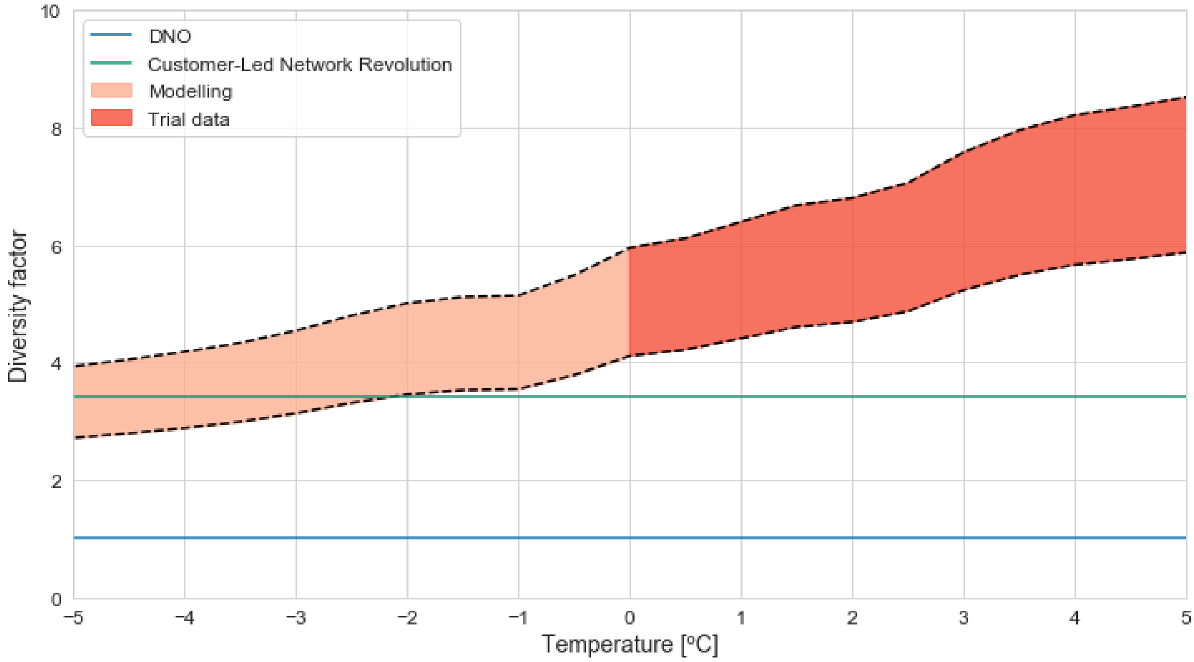


Figure 5-6: Comparison of the diversity factors of ASHPs for a temperature range of -5 to +5°C. The top dotted line corresponds to the diversity factor for detached houses and the bottom dotted line for terraced houses.

The diversity factor of ASHPs at -4.2°C and the coincidence factor of ASHPs were used in Equation 10 to estimate P, the 1-in-20 additional peak electricity demand on the GB power system produced by ASHPs in the electrification pathway in Cardiff, Swansea and Newport in 2050.

$$P = \frac{rated\ capacity \times Coincidence\ factor \times Number\ of\ units}{Diversity\ factor} \tag{10}$$

Equations 11 and 12 show the details of the calculation for Cardiff:

$$P_{upper} = \frac{3.82 \times 0.9 \times 119{,}590}{2.9} = 141{,}033\ kW \tag{11}$$

$$P_{lower} = \frac{3.82 \times 0.9 \times 119{,}590}{4.1} = 99{,}755\ kW \tag{12}$$

Table 5-1 shows the additional peak electricity demand on the GB power system for the three local authorities in 2050. In total, the ASHPs were estimated to increase the peak by 247 MW to 350 MW. This large interval may be explained by the average rated capacity of the ASHPs in 2050 in Cardiff, Swansea and Newport, which is closer to the value of terraced houses (5.5 kW) than detached houses (11 kW) in 2018 and thus closer to the upper bound than the lower bound.

Table 5-1: Calculated additional peak electricity demand on the GB power system from ASHPs using diversity factor and coincidence factor in Cardiff, Swansea and Newport in 2050 in the electrification pathway

	Cardiff	Swansea	Newport
Thermal output [kW]	3.82	4.20	4.06
Number of ASHPs	119,590	101,198	60,912
Additional 1-in-20 peak electricity demand from ASHPs upper bound [MW]	141	131	78
Additional 1-in-20 peak electricity demand from ASHPs lower bound [MW]	100	93	55

The same process can be followed to produce the ADMD values for resistance heaters and GSHPs to calculate the additional peak electricity demand of the aggregation of all individual heating technologies.

5.5 Study of the 1-in-20 Peak Electricity Demand of the Heat Decarbonisation Pathways

The half-hourly electricity demand for heat for the 1-in-20 peak demand day at LSOA level was produced for the three local authorities using the models from Chapter 4, the share of each heating technology in the electrification and hydrogen pathways, and the method from Section 5.2.1.

Figure 5-7 shows the aggregated peak electricity for heat demand in Cardiff, Swansea and Newport for the 1-in-20 peak demand day for 2018, 2030, 2040 and 2050 in the two pathways. The electricity peak demand increases from 28 MW in 2018 to 505 MW in 2050 for the electrification pathway and to 46 MW for the hydrogen pathway.

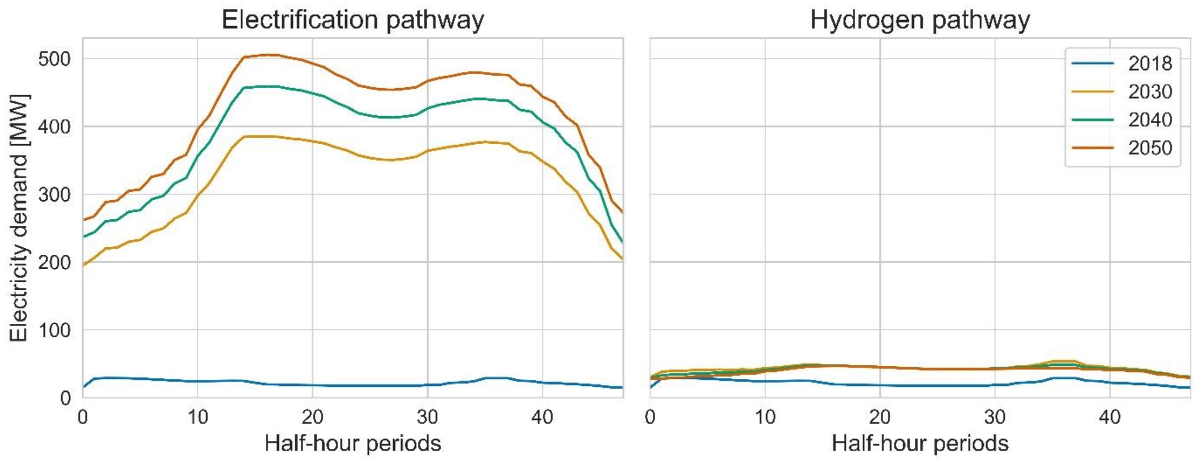


Figure 5-7: Half-hourly electricity demand for heating of Cardiff, Swansea and Newport during the 1-in-20 peak demand day for the modelled years in the electrification and hydrogen pathways.

Figure 5-8 shows how the half-hourly demand from Figure 5-7 is broken down between ASHPs, GSHPs and district heating units for the two decarbonisation pathways. The uptake of HPs in the electrification pathway is the reason for the large increase in the electricity peak demand.

Based on the ADMD calculation from Section 5.4 , the total 1-in-20 peak electricity demand from ASHPs in the electrification pathway was found to be [247, 350] MW at the time of the peak of the system. In Figure 5-8, this peak happens at the ca. 35 half-hour time-steps and is equal to 342 MW.

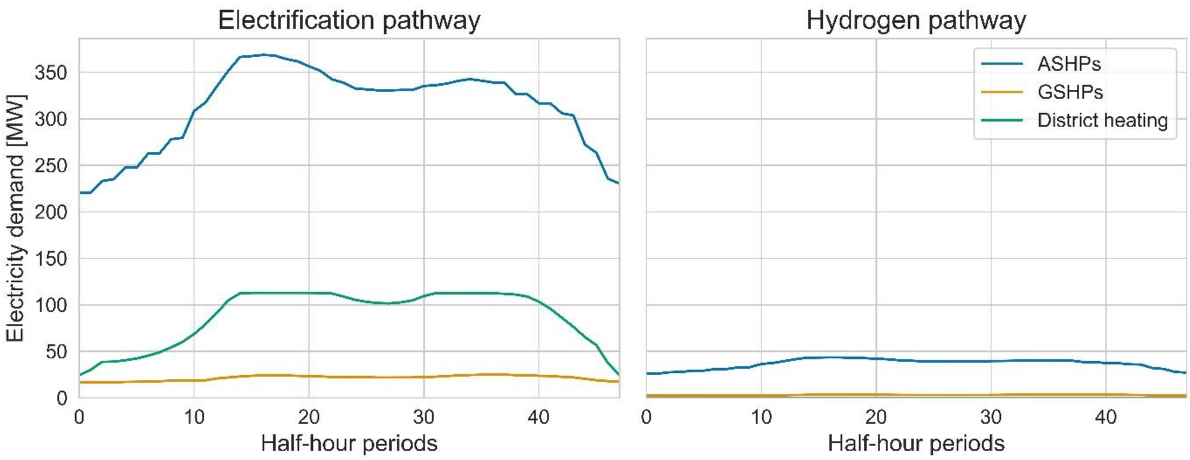


Figure 5-8: Half-hourly electricity demand for heating of ASHPs, GSHPs and district heating units for the 1-in-20 peak demand day in 2050 of the electrification and hydrogen pathways.

Table 5-2 and Table 5-3 show a comparison of the peak electricity demand for different years in each local authority for the two decarbonisation pathways. In the electrification pathway, the lower share of district heating in Swansea and Newport compared to Cardiff is reflected by a higher increase of the peak electricity demand from 2018 to 2050 in these two local authorities. This is due to the better efficiency of the district heating units and the capability to shift some of the demand to off-peak time using thermal storage. In the hydrogen pathway, no significant changes in the peak electricity demand were observed across the years. HPs were starting to replace resistance heaters, oil boilers, and biomass boilers in new dwellings but the improvements in the energy efficiency of the dwellings and the efficiency of the HPs counterbalanced their uptake.

Table 5-2: 1-in-20 peak electricity for heat demand for the electrification pathway (peak electricity demand in MW)

Year	Cardiff	Swansea	Newport
2018	16	8	5
2030	181	123	80
2040	209	154	97
2050	226	172	107

Table 5-3: 1-in-20 peak electricity for heat demand for the hydrogen pathway (peak electricity demand in MW)

Year	Cardiff	Swansea	Newport
2018	16	8	5
2030	21	21	12
2040	18	19	11
2050	17	18	11

Table 5-4 shows the peak hydrogen demand of the hydrogen pathways. Compared to the peak electricity demand of the electrification pathway shown in Table 5-2, the peak hydrogen demand is almost four times higher than the peak electricity demand. This can be explained by the difference in efficiency between hydrogen boilers and HPs (ASHPs, GSHPs and large-scale HPs) and the difference in the shape of the profiles between these technologies in Section 5.3

Table 5-4: 1-in-20 peak hydrogen for heat demand for the hydrogen pathway (peak electricity demand in MW)

Year	Cardiff	Swansea	Newport
2018	0	0	0
2030	0	0	0
2040	488	376	229
2050	862	658	406

The LSOAs in the three local authorities were matched to a primary substation using GIS software. The list of substations and their supply areas were provided by WPD (www.westernpower.co.uk). The LSOAs' profiles belonging to each substation were then aggregated and their peak was calculated.

Figure 5-9 shows the results for Cardiff in 2018, 2030, 2040 and 2050 for the electrification pathway. Those substations that have a higher peak in 2030 than in the other years (Canton, Cryws Road, Northcote Street, etc.) have most of their electricity for heat used through district heating schemes. The energy efficiency improvements that were considered to happen decrease these peaks in the years 2040 and 2050.

In the substations that supply areas using mostly HPs, a significant increase in the electricity peak demand is seen between 2018 and 2030. These peaks in electricity demand increase until 2050 following the conversion of more dwellings to HPs. The energy efficiency improvements of these dwellings are not sufficient to counterbalance the peak electricity demand increase driven by the uptake of the HPs. The figures for Swansea and Newport at substation level are available in Appendix E.3.

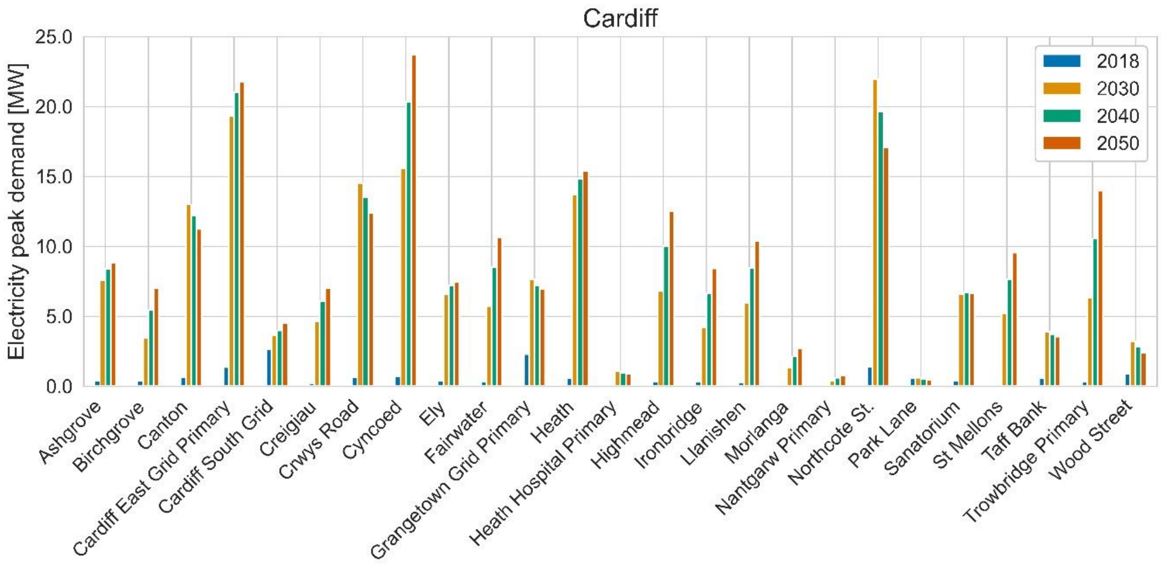


Figure 5-9: Peak electricity for heat demand in the electrification pathway for Cardiff

Figure 5-10 shows the results for the hydrogen pathway. Most substations see their peak electricity demand decrease, due to the combination of energy efficiency improvements and the replacement of resistance heaters with HPs. Those substations that show an increase in their peak electricity demand (Creigiau, Cyncoed, Fairwater, Ironbridge, etc.) supply areas where new dwellings using HPs are built between 2018 and 2050.

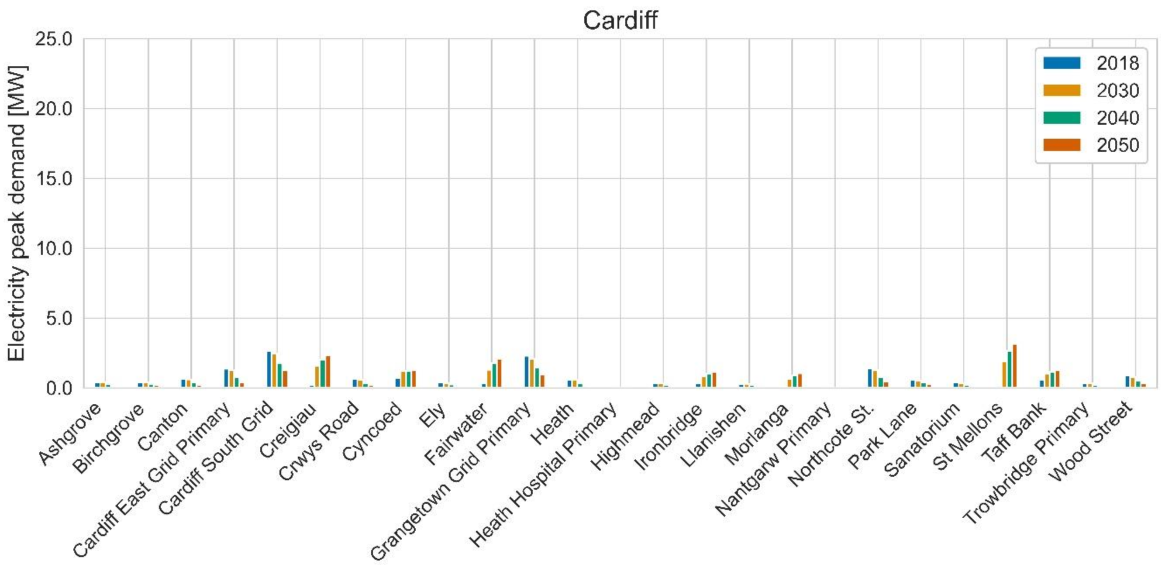


Figure 5-10: Peak electricity for heat demand in the hydrogen pathway for Cardiff

5.6 Summary

The half-hourly peak electricity demand for heating was studied in this chapter for different heating technologies and for the two heating decarbonisation pathways from Chapter 4.

Heating technologies were shown to be controlled in very different manners and their efficiency can be impacted by OAT (for ASHP and to a lesser extent GSHP), which leads to different peak times and different magnitudes of the peaks for each of them. HPs had a flatter operation and their peaks were two to three times lower than resistance heaters. In comparison, the peak energy demand of a gas boiler was more than three times higher than the ASHP.

When looking at individual technologies such as ASHPs, it was demonstrated that OAT is a key factor when calculating the ADMD. The ADMD of ASHPs at -4°C is more than 35% higher than at 0°C, and thus this is a factor to estimate the additional peak electricity demand by the installation of such technology.

In the electrification pathway, ASHPs were the main driver of the 18 times increase of the peak electricity demand between 2018 and 2050 followed by district heating and GSHPs. The peaks were heterogeneously reflected at substation level in Cardiff, Swansea and Newport. Several substations showed almost no changes in their peak electricity demand for heat, while around one fourth had a +20 MW increase. In comparison, there was an only ca. two times increase of the peak electricity demand in the hydrogen pathway.

When comparing peak demand of secondary energy resources (electricity and hydrogen), the peak energy demand of the electrification pathway was four times lower than the peak energy demand of the hydrogen pathways by 2050, due to the differences in the efficiency of HPs and hydrogen boilers.

6 The Heat Supply Options Assessment Model

6.1 INTRODUCTION

The viability of heat decarbonisation pathways not only depends on their costs and performance but is also significantly affected by the local circumstances, such as availability of space and level of insulation in buildings, heat demand density in an area [10], the availability of waste heat [25] and existing energy infrastructure (e.g., connection to the gas grid and availability of capacity in the electricity network) [26].

This chapter will describe a model to assess heat supply options for local areas by considering different gas and electricity price scenarios, as well as local circumstances. The local authority of Neath Port Talbot in Wales was used as an example.

6.2 METHODOLOGY

Figure 6-1 shows the methods developed in this research and how they interact with each other. The heat supply options assessment (HSOA) model that is developed in this chapter has two main steps:

1. Constructing a **district heating system model** using inputs of local area data, techno-economic data and estimated heat demand.
2. Constructing an **individual heating systems optimisation model** using inputs of local area data, techno-economic data and estimated heat demand.

To assess the heat supply options, the annualised costs of the district heating system and individual heating systems were compared and the option with the lowest annualised cost was selected as the cost-effective way to decarbonise the heat supply in a selected area. Indicators such as CO2 emissions, the number of heating technologies and the levelized cost of heat were calculated.

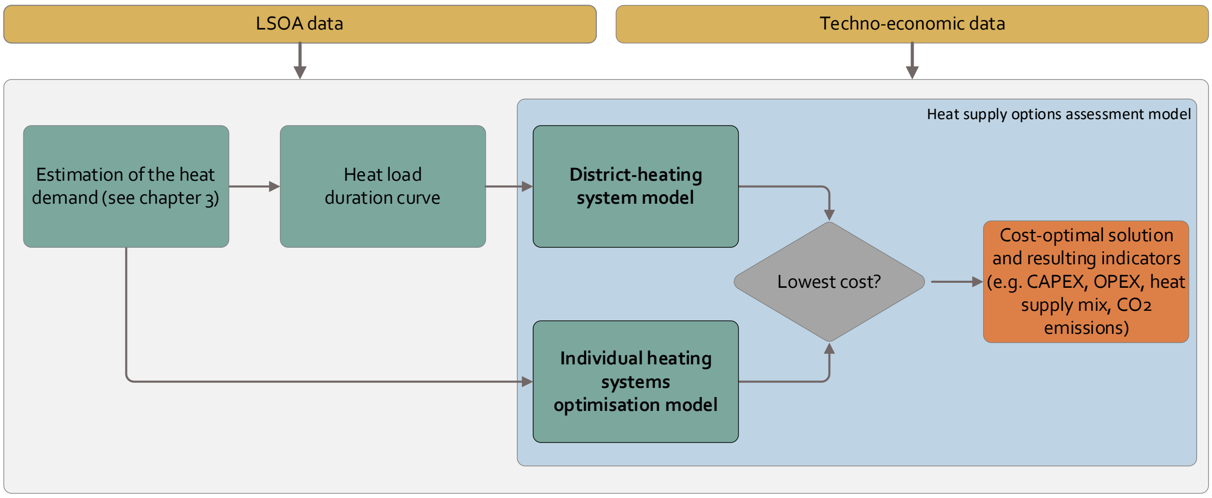


Figure 6-1: Overview of the methodology of this study

6.2.1 The District Heating System Model

The cost related to a district heating scheme is the cost for the heat supply S and the cost for the heat distribution D. The annual expenditure was calculated using Equation 13.

$$Annual\ expenditure = (S_{CAPEX} + D_{CAPEX}) \times \frac{DR}{1-(1+DR)^{-n}} + S_{OPEX} + D_{OPEX} \qquad (13)$$

Where DR is the discount rate (4%) and n is the lifespan of the district heating system (40 years).

6.2.1.1 The Heat Supply Costs of District Heating Systems

The technologies considered to supply heat to a district heating system included gas boilers, gas CHP units and large-scale HPs. The installed capacities for these technologies were calculated by identifying the combination that minimised the annual heat supply cost. The methodology used is drawn from [70] and it combines the use of screening curves with load duration curve. The screening curves are used to compare technologies in terms of cost and full load hours. This information transposed on to the load duration curve is used to calculate the capacity installed and the heat demand supplied. This information is then used to calculate the CAPEX and OPEX of the heat supply.

6.2.1.2 The Heat Distribution Network Costs

The cost of the district heating network in each local area was determined by the length of the pipes, their diameter and the type of area (e.g., rural, urban). Equation 14 was used to calculate the average pipe diameter of a district heating scheme for a local area, where $Q_{local\ area}$ $[GJ]$ is the heat sold in the local area, L $[m]$ is the length of network and $Q_{local\ area}/L$ is the linear heat density. This equation was derived by [80] through fitting a logarithmic function to estimate the relationship between average pipe diameter $d_a[m]$ and linear heat density $[GJ/m]$ of 134 district heating schemes in Sweden.

$$d_a = 0.0486 \times ln(Q_{local\ area}/L) + 0.0007 \qquad (14)$$

In this paper, the heat sold is assumed to be equivalent to the heat demand and the length of the local road network is used as a proxy for the length of the pipes. The length of the road in each LSOA was calculated from the OS open road data[81], excluding motorways and road classified as A road, combined with the boundaries of the LSOAs using a GIS software.

According to [70], the heat distribution network cost D_{CAPEX} is a function of the average pipe diameter, the length of the network and the area characteristics, as defined by Equation 15.

$$D_{CAPEX} = (C_1 + C_2 \times d_a) \times L \qquad (15)$$

Where C_1 and C_2 are the construction costs of heat networks for the local area shown in Table 6-1. These costs were adapted from [80], which estimated them from district heating systems built in Sweden. The original costs were converted from Euros to British pounds using a 0.88 €/£ exchange rate, and the area characteristics renamed to fit the UK classification for the level of the urbanisation of local areas.

Local area characteristics	**C1 [£/m]**	**C2 [£/m²]**
Urban > 10k	252	1,779
Village, town and fringe	188	1,518
Hamlet & isolated dwellings	133	1,213

Table 6-1: Construction cost by local area characteristics.

As shown by Equation 16, the variable cost of 0.361 £/GJ was assumed for heat supplied by district heating networks [82]. The variable cost accounts for the electricity consumption of pumps and heat losses (heat losses estimated at 8% of the supplied heat). This is a simplification which considers that, regardless of the system characteristics, the consumption of electricity for pumping water in the network is proportional to the heat supplied.

$$D_{OPEX} = Q_{local\ area} \times (1 + 0.008) \times 0.361 \qquad (16)$$

The cost of the substation that links the district heating network to the building heating system was also considered. The major driver for these connection costs is the dwelling type. For a flat, the costs are shared by the other flats of the building, thus it does not cost as much as for connecting a house. In this paper, the average figures from [83] were used for the connection costs: £7218 or £649 equivalent annual cost for houses and £4621 or £416 equivalent annual cost for flats. This costs do not include the cost of heat.

6.2.2 The Individual Heating Systems Model

As an alternative to district heating, possible heating systems for individual dwellings were assessed using an optimisation model. The objective of the model was to find the cost-optimal individual heating technology for each dwelling category in a local area.

The annual expenditure of the cost-optimal individual heating systems for a local area was calculated as the sum of the equivalent annual CAPEX (I_{CAPEX}), the annual OPEX (I_{OPEX}) and the annual cost of reinforcements of the power sector (I_{RC}) , as shown by Equation 17.

$$Annual\ expenditure = I_{CAPEX} + I_{OPEX} + I_{RC} \tag{17}$$

The problem was formulated as a mixed-integer linear programming where the objective was to minimise the annual expenditure of the system, as shown by Equation 18. This was implemented in Python using the Pyomo optimisation modelling language [84], [85] and the IBM CPLEX solver.

$$Obj\!: \min\ Z = (I_{CAPEX} + I_{OPEX} + I_{RC}) \tag{18}$$

$$I_{CAPEX} = \sum_{f} \sum_{d} \left[EAC_{f,d} \times N_{f,d}\right] \tag{19}$$

$$I_{OPEX} = \sum_{f} \sum_{d} \left[\frac{Q_d}{\eta_f} \times O_{f,d} \times N_{f,d}\right] \tag{20}$$

$$I_{RC} = \sum_{f} \sum_{d} \left[ADMD_{f,d} \times RC \times N_{f,d}\right] \tag{21}$$

Z is the cost function.

$d \in dwelling\_\mathrm{arche}type$.

$f \in future\_tech$ is the list of technologies by which current heating technologies can be replaced, which includes gas boilers, resistance heaters, biomass boilers, ASHP, GSHP with borehole and HHPs.

$EAC_{f,d}$ is the equivalent annual cost of technology f in the dwelling category d that includes the cost of capital and the fixed annual operation and maintenance cost. Q_d is the annual heat demand of the dwelling category d. η_f is the efficiency of the technology f. O_f is the variable operation cost (£/kWh) of technology f which includes the fuel costs and CO_2 costs minus any incentives. $N_{f,d}$ is the number of dwellings corresponding to category d where the future technology f is installed. $ADMD_{f,d}$ (kW) is the after-diversity maximum electricity demand of the technology f installed in the dwelling category d. Finally, RC is the network reinforcement cost (£/kW) to cover the potential increase of the peak of electricity demand.

One of the constraints of the model is that gas-based technologies cannot be installed in a dwelling not connected to the gas grid. This was implemented by setting to zero the number of dwellings not connected to the gas grid and being converted to a heating technology using natural gas. In addition, the number of dwellings with biomass boilers in urban areas cannot increase. Therefore, the number of dwelling categories where the heating technology was biomass boiler in the input data was set to be below or equal to the number in the output of the model. Other constraints were enforced through cost and choice of the list of future technologies. When a technology was unlikely to be installed in a specific type of dwelling, the cost of this unit was set high (see appendix F.4). Future technologies did not include oil boilers.

6.3 Example of Neath Port Talbot

The HSOA model was demonstrated on the local authority of Neath Port Talbot (NPT) in Wales. NPT has a mix of rural and urban areas that are not all connected to the gas grid. NPT was divided into 91 local areas (LSOAs) using the UK geographic system for statistics. For each of these LSOAs, the number of dwellings, their types and their heating systems in 2011 were extracted from the publicly available statistics [1].

Figure 6-2 shows the number of heating installations by dwelling type currently used in NPT [1]. Gas boilers are the dominant heating technology. Semi-detached and terraced dwellings are the main dwelling types. There is a total of 57,891 dwellings in NPT. This data was used to define 16 dwelling categories, with a dwelling category being the combination of a dwelling type and a heating system.

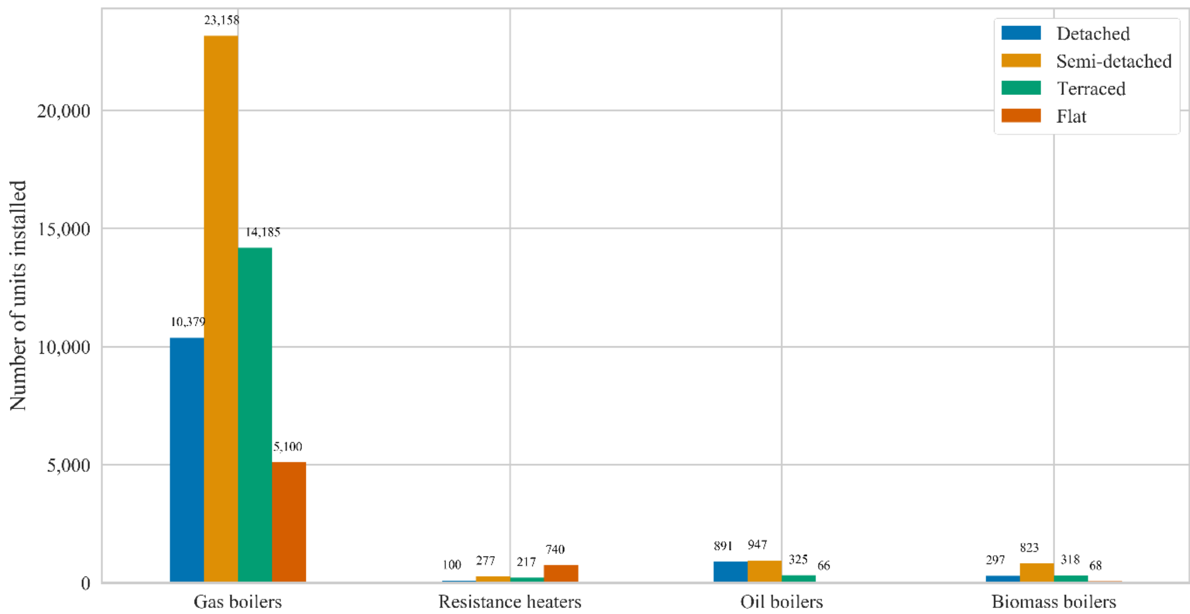


Figure 6-2: Heating currently installed in dwelling types in Neath Port Talbot

Figure 6-3 shows the current share of gas, oil and biomass boilers based on the total number of dwellings in each LSOA. The LSOAs with a low share of gas boilers have fewer dwellings connected to the gas grid. Oil and biomass boilers most commonly used where there is no gas connection.

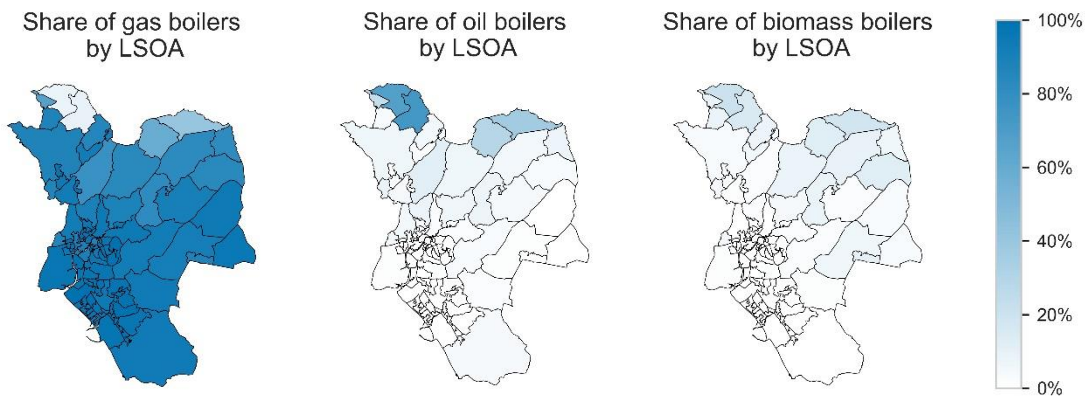


Figure 6-3: Maps of Neath Port Talbot showing the current share of heating technologies

6.3.1 Heat Demand of Dwellings in Neath Port Talbot

The EPC certificates for NPT [86] were collected and mapped to the 91 LSOAs and the heat demand by LSOA was calculated as described in Chapter 3. Figure 6-4 shows the estimated average annual heat demand by dwelling category in NPT. Detached dwellings have the highest heat demand on average, followed by semi-detached, terraced and flats. For a given dwelling type, the annual heat demand varies depending on the heating fuel used. This can be explained by the differences in the characteristics of these dwelling categories, including the age of the dwelling, gross internal area, and energy efficiency level. For instance, detached dwellings with resistance heaters are on average smaller in size and more energy-efficient than detached dwellings with oil boilers.

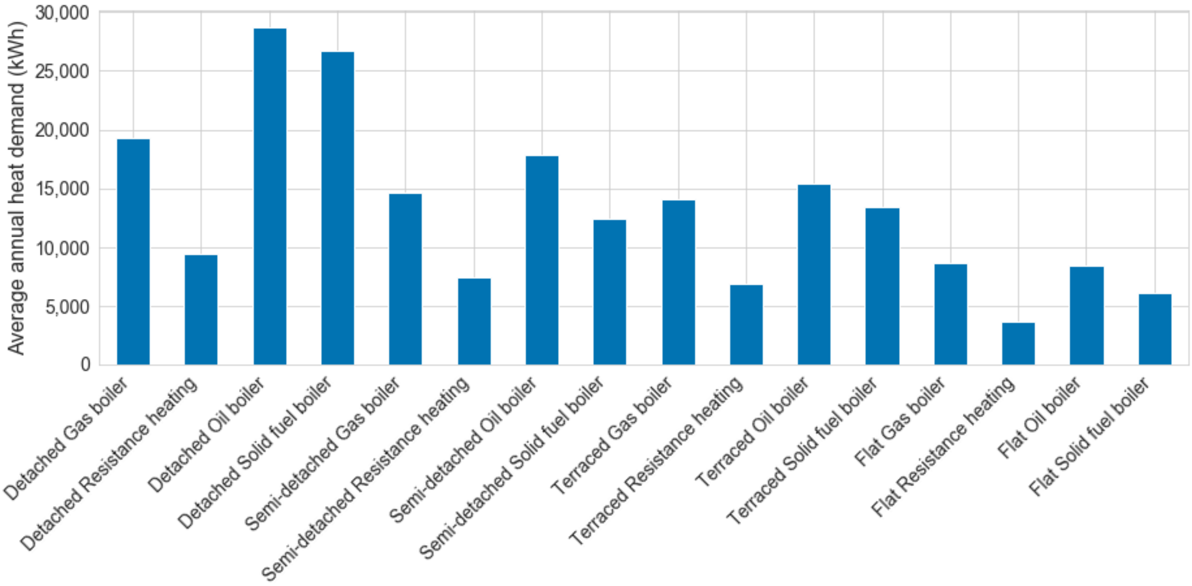


Figure 6-4: Average annual heat demand by dwelling categories in Neath Port Talbot produced using the EPC-based method.

The total heat demand for each LSOA was derived by multiplying the heat demand of each dwelling category by the number of dwellings in that category known from the 2011 census data [1]. Figure 6-5 shows that the estimated heat demand in NPT for each LSOA ranges from 6,390 MWh to 16,850 MWh.

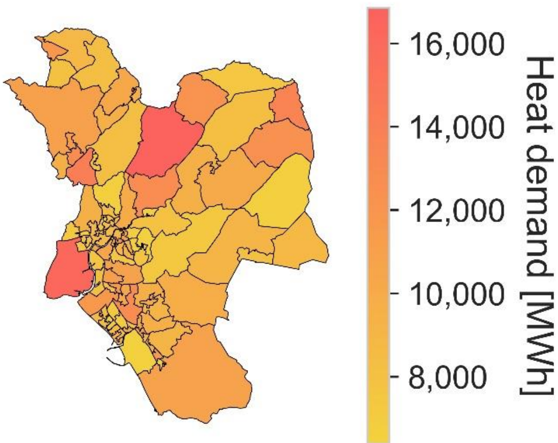


Figure 6-5: Map of Neath Port Talbot showing the estimated heat demand for each LSOA

6.3.1.1 Assessment of Heat Supply Options in Neath Port Talbot

Using the HSOA model shown in Section 6.2 , cost-optimal heat supply technologies were determined for each of the 91 LSOAs in NPT for different combinations of electricity and gas prices. The input data for the modelling, which includes the techno-economic data of the heating technologies, is available in Appendix F. The resulting heating technologies, carbon intensity and levelized cost of heat at local authority level are presented, followed by the spatial results for two combinations of electricity and gas prices.

6.3.1.2 Scenario Definition

Figure 6-6 shows the 90 possibilities of gas and electricity prices with each dot representing a scenario, which are referred to as '*price scenarios*' hereafter. The changes in biomass and oil prices were assumed to be proportional to the changes in the gas price. The remaining assumptions and input parameters to the models are listed in the Appendix F. As a point of reference, the prices for 2018 were: 17.9 p/kWh for electricity [87], 4.4 p/kWh for natural gas [87], 5 p/kWh for biomass [88] and 5 p/kWh for oil [87]. The closest *price scenario* to the 2018 prices is the scenario where the electricity price is 17 p/kWh and the gas price is 4 p/kWh. This is referred to as the '*2018 price scenario*' and is shown as a red cross in Figure 6-6 to Figure 6-9.

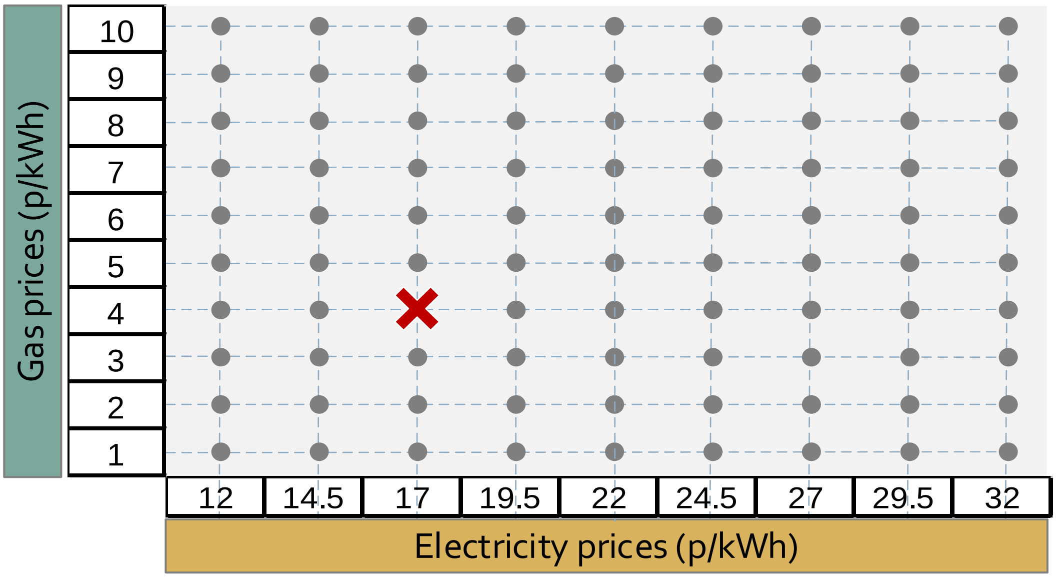


Figure 6-6: Combinations of electricity and gas prices modelled to create price scenarios.

The results for NPT were then produced by aggregating the results of the NPT LSOAs for each price scenario.

6.3.1.3 The Heating Technologies

Figure 6-7 shows the two technologies with the largest shares of heat supplied for each price scenario. The two prevalent heating technologies are referred to as the main and secondary technologies. Low gas prices favour gas-based technologies, whereas high gas prices favour electricity-based technologies. For the *2018 price scenario*, the main technology chosen is the gas boiler and the secondary technology is a biomass boiler, which shows that the model's output is similar to the real situation in 2018.

When the gas price increases, electricity-based technologies become more attractive. This is shown by the red (6), purple (7) and blue (3) areas, where individual ASHPs and district heating using large-scale HPs are chosen as either main or secondary technologies. In contrast, when the electricity price increases, the pink (9), brown (8) and green (5) areas that show gas-based technologies become attractive.

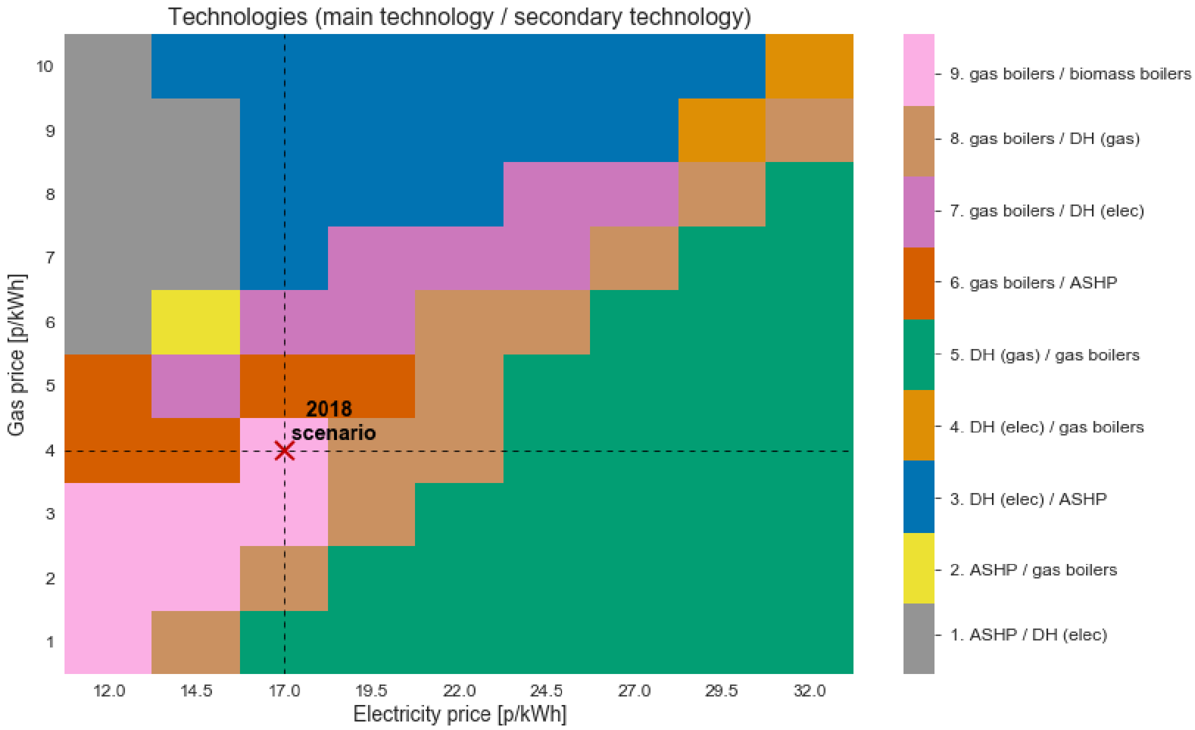


Figure 6-7: Colour map displaying the main and secondary technologies for each price scenario (each rectangle represents one price scenario). DH stands for District Heating.

6.3.1.4 The Carbon Intensity of Heat

Figure 6-8 has two areas, showing where the carbon intensity of the price scenarios is below and above the intermediate target of 180 gCO2/kWh suggested by the CCC. The only price scenarios to meet this target are the scenario with an electricity to gas price ratio below 2.4 or the scenario with gas prices over 5 p/kWh. The scatter points correspond to historical prices (+), 2018 prices (x) and projected prices (D) from BEIS [4]. BEIS used these prices in an econometric model to project the UK energy demand and greenhouse gas emissions, which was used to assess the progress towards the UK emissions targets. It was observed that all the price scenarios close to past, present and projected prices have a carbon intensity above 180 gCO2/kWh.

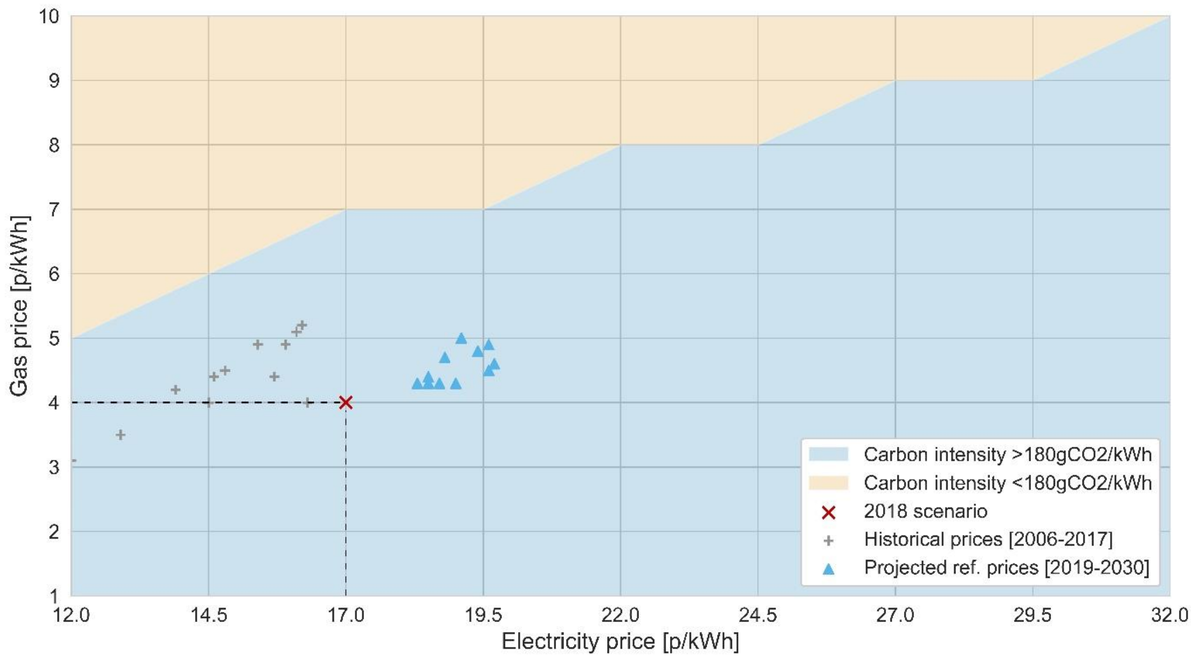


Figure 6-8: Carbon intensity of the price scenarios. The carbon intensity values were interpolated for those energy prices that were not modelled.

6.3.1.5 The Levelized Cost of Heat

The levelized cost of heat (LCOH) was used to assess and compare technologies with different characteristics, such as lifetime, CAPEX and OPEX. Equation 22 was used to calculate the LCOH for NPT:

$$LCOH_{NPT} = \frac{CAPEX_{NPT} + OPEX_{NPT}}{Heat\ demand_{NPT}} \tag{22}$$

For the *2018 price scenario*, the LCOH was 6.9 p/kWh$_{thermal}$. This value was used as a point of reference to calculate the relative percentage change of the LCOH for different price scenarios; as shown by Equation 23:

$$LCOH\ change\ (\%) = \frac{LCOH_{scenario}}{LCOH_{2018}} - 1 \tag{23}$$

Figure 6-9 shows four levels of LCOH change of the price scenarios using contour lines, which are displayed overlaying the carbon intensity areas shown in Figure 6-8. The price scenarios that are close to the 0% line (i.e. negligible changes in LCOH compared to the *2018 price scenario*) have a gas price between 0.04 and 6 p/kWh. When the gas prices are higher, the LCOH change gets closer to +25% and can rise to more than +50%.

The price scenarios that meet the carbon intensity target shows a LCOH change of less than +25% if the electricity price is below 15 p/kWh and the gas prices are above 5 p/kWh. If the electricity price is the same as in the 2018 price scenario (17 p/kWh), then the gas prices are above 7 p/kWh and the LCOH change is above +25%. The price scenarios annotated as points 1 and 2 are close to the 2018 price scenario and will be studied in the next section.

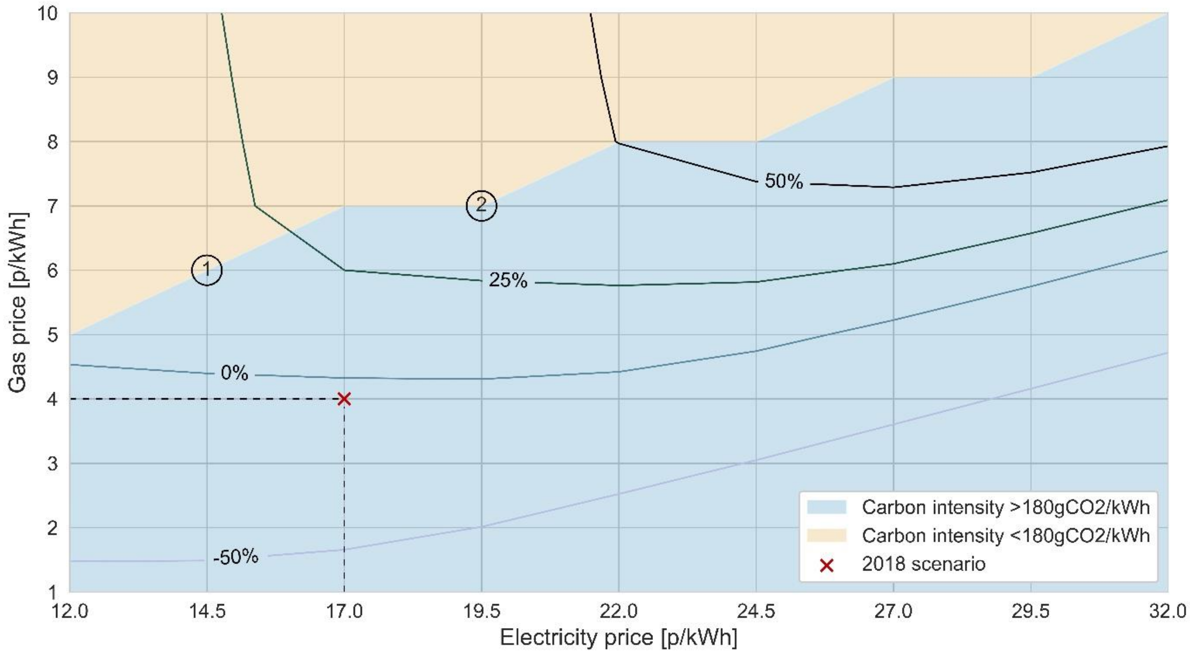


Figure 6-9: Contour lines showing the percentage change of the LCOH of the price scenarios compared to the 2018 scenario.

6.3.1.6 Spatial Comparison of Two Price Scenarios

Table 6-2 lists the characteristics of price scenarios 1 and 2, which meet the intermediate carbon intensity target.

Table 6-2: Characteristics of the two price scenarios selected

	Electricity price (p/kWh)	Gas price (p/kWh)	Percentage change of the LCOH	Carbon intensity (gCO2/kWh)
Scenario 1	14.5	6	20%	131
Scenario 2	19.5	7	39%	140

In Price Scenario 1, the main fuel for heating is electricity (see Figure 6-7) with 28% of heat supplied by ASHPs and 29% supplied by large HPs in district heating. The remaining heat demand is supplied by gas boilers (40%) and biomass boilers (3%). In Price Scenario 2, 15% of heat is supplied by ASHPS and 37% by large HPs in district heating. The remaining heat demand is supplied by gas boilers (45%) and biomass boilers (3%). The increase in district heating share is explained by the higher energy prices making this technology more viable than in the Price Scenario 1.

Figure 6-10 shows the share of heating technologies by LSOA for the two price scenarios. The adoption of the technologies is different in each LSOA. The LSOAs with higher linear heat density are converted to district heating. ASHPs and gas boilers supply the heat in the other LSOAs.

The share of ASHPs and gas boilers varies from one LSOA to another due to the type of buildings and heat demand. In Price Scenario 1, 16 LSOAs have a share of ASHPs above 80% which leads to LSOAs not requiring a gas grid for heating anymore. This is not as significant in Price Scenario 2, where gas boilers remain dominant outside of the LSOAs converted to district heating. This reflects that heat decarbonisation is not happening at the same rate in every LSOAs.

The increase of gas and electricity prices from Price Scenario 1 to 2 does not change the core set of LSOAs viable for district heating. The LSOAs viable for district heating in Price Scenario 1 are also viable for district heating in Price Scenario 2. Hence, converting these LSOAs to district heating could be considered as a low regret path when looking at energy planning strategies.

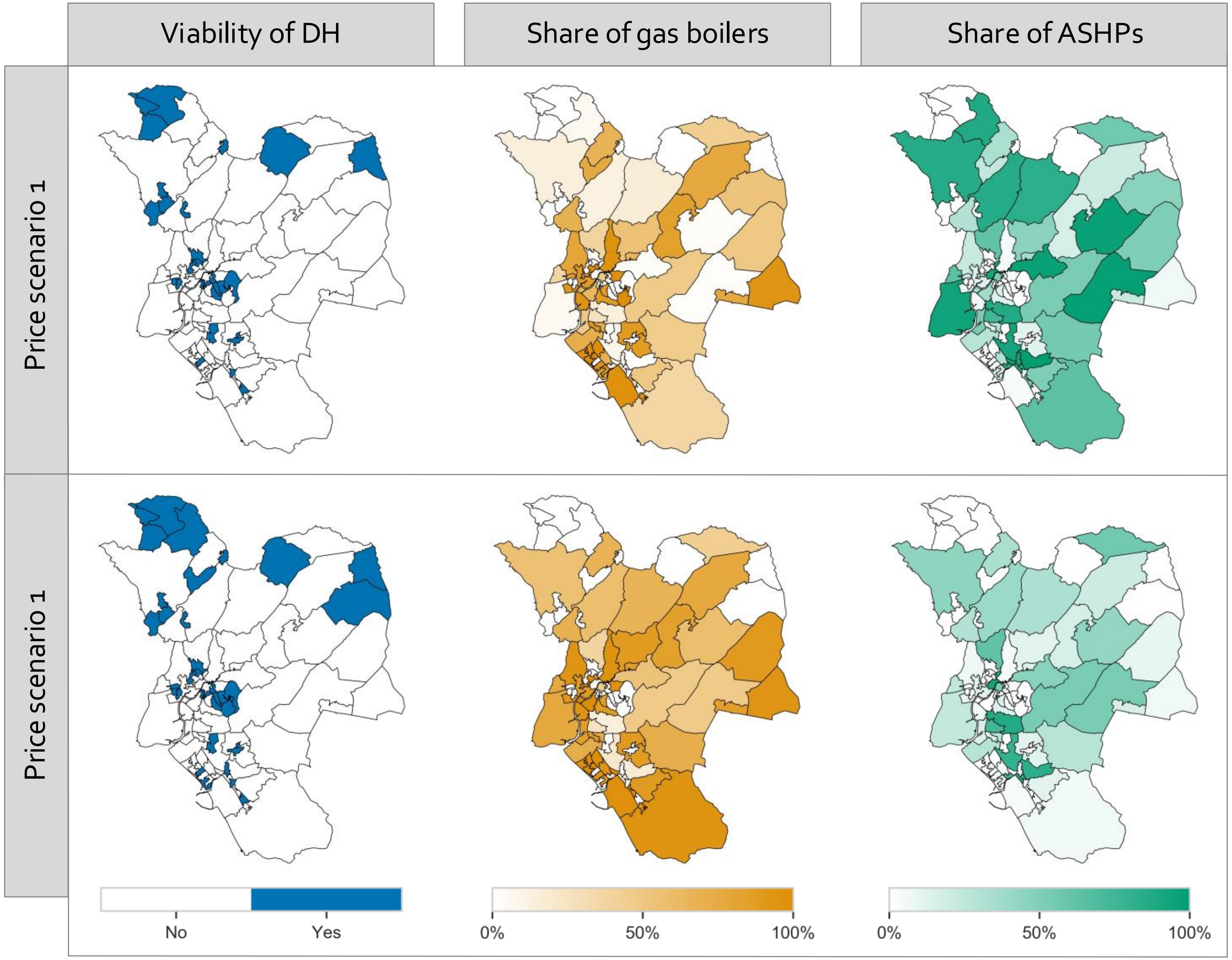


Figure 6-10: Heating technology uptake at LSOA level for Price Scenario 1 and 2.

6.4 SUMMARY

This section discusses the uncertainties regarding the input data, the limitations of the HSOA model and a summary of the key findings of the application of the model on NPT.

6.4.1 Uncertainties of the input data

To deal with uncertainties regarding fuel prices and take decisions regarding the future heating technologies, the HSOA model was designed to be run using several fuel prices scenarios. The analysis of these results provide information about the heat supply options which are common to most scenarios. These options are considered the most robust. For instance, if ASHPs are chosen has the most cost-effective solution for the same dwelling category across three out of five fuel price scenarios with the same likelihood of happening, this technology should be selected as the final choice for this dwelling category.

This approach can be improved by identifying the most likely fuel prices scenarios instead of weighting all fuel price scenarios equally. This improved approach was demonstrated in Chapter 7.

A similar approach can be applied to other input data that carry uncertainties such as:

- the current heat demand of each dwelling category – sensitivity required around the errors in the estimated annual heat demand from the EPC-based method from Chapter 3 and the potential heat demand savings from energy efficiency measures,
- the future heat demand – by how much energy efficiency measures or changes in behaviours could decrease the current heat demand and how would that impact the choice of heating technologies (e.g., would an ASHP still the most economically viable option if the heat demand is decreased by 30%),
- the building stock information – for instance, the results shown for NPT are based on the building stock data from 2011 thus there are uncertainties regarding the change of this stock since and how this would impact the results obtained.

6.4.2 Limitation of the modelling approach

There are limitations to the HSOA model. One limitation is that the model does not allow the heat demand for a LSOA to be partly supplied by district heating and partly supplied by individual heating technologies. However, a cost-effective solution for a LSOA may not be a cost-effective solution for all the dwellings within this LSOA. For instance, in a LSOA where district heating is the chosen solution, there may be individual dwellings which will be paying more than with their current heating systems. This problem could be decreased by running the model on smaller local areas than LSOAs. However, the availability of data could be a barrier to running such scenarios.

Furthermore, the HSOA model does not consider the dispatch of heat at high resolution only at yearly resolution. Hence it does not account for the value of flexibility and the potential that could exist to shift the demand from one hour to another which could favour hybrid technologies such as hybrid heat pumps or district heating with different X-to heat technologies or the use of thermal storage.

6.4.3 Key findings from the results of the HSOA model applied to Neath Port Talbot

The capabilities of the model for investigating optimal heat supply options at local area level were presented. From a high-level point of view, it was observed that in NPT:

- The current mix of heat supply based on gas boilers cannot meet the intermediate target of 180 $gCO2/kWh_{thermal}$ suggested by the CCC.
- The gas price needs to be higher than 5 p/kWh to start driving the replacement of gas boilers and thus the decarbonisation of heat.
- The two key technologies identified for the decarbonisation of heat are district heating with large heat pumps and ASHPs in buildings.
- HHPs and GSHPs are not chosen by the model because of their higher costs compared to other technologies.
- The changes in technology and energy prices required to decarbonise heat will lead to an increase of the LCOH, this increase could be above 25%.

It was shown that the share of gas boilers could significantly decrease in some LSOAs. This could affect the economic viability of maintaining a low-pressure gas network and require reinforcement of the electricity network depending on the technology replacing them. Further challenges include potential bottlenecks in the supply chain to replace the gas boilers in a large number of dwellings with heat pumps and/or to build a district heating network.

7 Developing Heat Decarbonisation Pathways Using Cost Analysis and the Heat Supply Options Assessment Model

7.1 INTRODUCTION

The electrification and hydrogen pathways provided extreme perspectives of what heat decarbonisation could look like in Cardiff, Swansea and Newport. The model developed in Chapter 6 provided a third example, which represented a cost-optimal heat decarbonisation pathway. When applied to NPT, the model showed that the two key technologies to decarbonise heat by 2030 are district heating and electrification of heat.

In this chapter, the focus is on 2050, the year by which the UK aims to reach its carbon neutrality target. As with every long-term analysis, there are many uncertainties regarding the fuel prices, the costs of different technologies, the level of decarbonisation of the electricity and hydrogen networks, and so on. To help with decision making, two objectives will be defined and discussed in this chapter:

1. A comparison of the costs of the electrification and hydrogen pathways, including their fuel price sensitivity.
2. Identify low regret options using the heat supply options (HSOA) model developed in Chapter 6.

7.2 COST COMPARISON AND FUEL PRICE SENSITIVITY OF THE ELECTRIFICATION AND HYDROGEN PATHWAYS

The cost of the two pathways is broken down into two components: the dwelling-side costs and the system-side costs. Figure 7-1 shows the scope of each component. The dwelling-side costs include the capital and operational costs of the individual heating units, the district heating generation units and the district heating substations installed in dwellings. The district heating generation units are included in the dwelling-side costs to enable them to be compared to other technologies. The system-side costs included the costs of the hydrogen, electricity and heat distribution networks. These costs are calculated using the number of units installed, their heat production and the other parameters extracted for the two pathways.

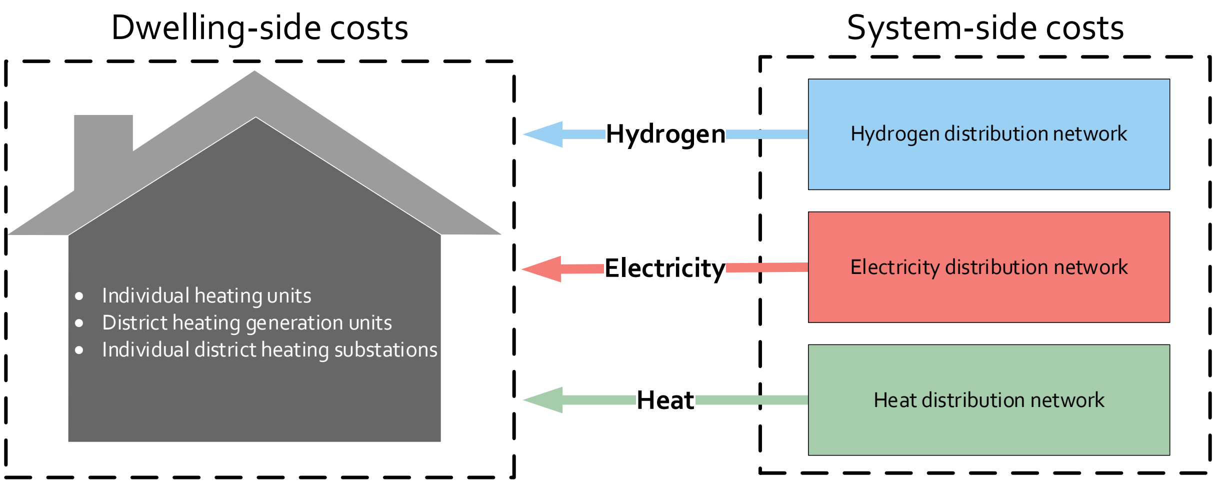


Figure 7-1: Illustration of the breakdown of the cost of the heat decarbonisation pathway into two components.

Given that a large share of the cost of these pathways is driven by the electricity and hydrogen prices, nine energy price scenarios are defined and used to calculate the cost of the two pathways. The dwelling-side and system-side costs of the three local authorities are annualised and summed, they will then be compared and discussed.

7.2.1 Dwelling-side Costs

The dwelling-side costs include the capital and operational costs related to the individual heating units, the district heating generation units and the district heating substations installed in dwellings. The capital costs include the cost of the unit and the costs for decommissioning one unit and replacing it with another. The operational costs are the costs of the energy used by the unit and its maintenance. Table 7-1 and Table 7-2 show the technical and economic data of the units. Individual hybrid heating systems such as individual hybrid heat pumps were not considered in this section. The results obtained in Section 6.3 with Neath Port Talbot showed that the capital investment of these units were too high compared to the other heating technologies for being chosen by the HSOA model.

Table 7-1: Cost of district heating units. OPEX: Operation and Maintenance

Technology	Lifetime [years]	CAPEX [GBP/MW]	Fixed OPEX [GBP/MW/year]	Variable OPEX [GBP/MWh] (excl. fuel costs)	Efficiency heat	Source
Electric boiler	20	114,400	810	0.9	99%	[3]
Geothermal heat pump	25	2,094,400	17,512	5.2	494%	Geothermal heat-only plant with electric heat pump, 1200m. DH temp. 80/40˚C [3]
Energy from waste (only for Cardiff)	25	160,423	44,704	5	75%	[3] Efficiency calculated using [71], [89]

Table 7-2: Costs of Individual Heating Technologies

Technology	Dwelling type	Lifetime [years]	CAPEX[GBP/unit]	Fixed OPEX [GBP/year]	Auxiliary electricity consumption [kWh/year]	Efficiency heat	Sources
Hydrogen boiler	Flat	20	3,381	244	150	84%	[18]
Hydrogen boiler	Detached	20	3,381	244	150	84%	[18]
Hydrogen boiler	Semi-detached	20	3,381	244	150	84%	[18]

Technology	Dwelling type	Lifetime [years]	CAPEX[GBP/unit]	Fixed OPEX [GBP/year]	Auxiliary electricity consumption [kWh/year]	Efficiency heat	Sources
Hydrogen boiler	Terraced	20	3,381	244	150	84%	[18]
Resistance heating	Flat	30	1,500	21	0	100%	[20]
Resistance heating	Detached	30	3,150	25	0	100%	[57]
Resistance heating	Semi-detached	30	2,024	21	0	100%	[90]
Resistance heating	Terraced	30	2,024	21	0	100%	[90]
ASHP	Flat	18	2,400	60	100	250%	1 bedroom flat (1 x 2 kW for bedroom + 1 x 3.5 kW for lounge) - lower cost of fittings used due to smaller install [91]
ASHP	Detached	18	8,750	60	100	250%	8kW ASHP fully installed including fittings, small buffer tank and cylinder, controls and heat distribution system (new for a smaller house) [91]
ASHP	Semi-detached	18	8,750	60	100	250%	Same as for ASHP detached
ASHP	Terraced	18	8,750	60	100	250%	Same as for ASHP detached

Technology	Dwelling type	Lifetime [years]	CAPEX[GBP/unit]	Fixed OPEX [GBP/year]	Auxiliary electricity consumption [kWh/year]	Efficiency heat	Sources
GSHP	Detached	20	13,200	85	100	380%	8kW ground source heat pump (GSHP) fully installed including small buffer tank and cylinder but excluding ground works and excluding controls, excluding the heat distribution system + cost of ground work [91]
GSHP	Semi-detached	20	13,200	85	100	380%	Same as for GSHP detached
Gas boiler	Flat	20	2,000	75	150	84%	Cheapest option from: [92]
Gas boiler	Detached	20	4,000	75	150	84%	more expensive option: [92]
Gas boiler	Semi-detached	20	2,650	75	150	84%	close to the average figures supplied by [92]
Gas boiler	Terraced	20	2,650	75	150	84%	close to the average figures supplied by [92]
Oil boiler	Flat	20	3,560	100	140	84%	could not find costs for flats so used same costs than for other dwelling types.
Oil boiler	Detached	20	3,560	206	140	84%	21kW combi for combi direct swap (including labour and fittings but excluding controls and heat distribution system, assuming most of the existing fittings can be used) [91]
Oil boiler	Semi-detached	20	3,560	100	140	84%	Same as for oil boiler detached
Oil boiler	Terraced	20	3,560	100	140	84%	Same as for oil boiler detached

Technology	Dwelling type	Lifetime [years]	CAPEX[GBP/unit]	Fixed OPEX [GBP/year]	Auxiliary electricity consumption [kWh/year]	Efficiency heat	Sources
Biomass boiler	Flat	20	10,000	429	240	82%	could not find costs for flats so used same costs than for other dwelling types.
Biomass boiler	Detached	20	10,000	429	240	82%	25kW lower - quality / cheaper boiler fully installed - excluding pellet store, no additional control and excluding heat distribution system [91]
Biomass boiler	Semi-detached	20	10,000	429	240	82%	Same as for biomass boiler detached
Biomass boiler	Terraced	20	10,000	429	240	82%	Same as for biomass boiler detached

The capital costs of individual heating units is based on the average size of heating systems in 2050, which is estimated from the average heat demand of different dwelling type in the electrification and hydrogen pathways.

Table 7-3 shows how the average size of heating systems changed from 2018 to 2050, due to energy efficiency improvements in the dwellings using the results from Chapter 3. A decrease of 25-30% in the size of the units can be observed between 2018 and 2050.

Table 7-3: Unweighted average size of heating systems by dwelling type in 2018, 2030, 2040 and 2050. Average size of heating system (kW_{th}).

Dwelling types	2018	2030	2040	2050
Detached	10	9	8	7
Semi-detached	8	7	6	6
Terraced	8	7	6	5
Flat	4	3	3	3

The operational costs of the individual heating units were calculated based on the heat produced by each technology in 2050, which also decreased by 25-30%.

The capital costs of district heating substations were £4,224 for houses and £1,584 for flats based on data from [90]. For comparison purposes, the capital and operational costs of the district heating units are also added to the dwelling-side costs. The size of the units and their heat production for each LSOA was extracted from the electrification pathways data produced in Chapter 4. No district heating was considered in the hydrogen pathways.

7.2.2 System-side Costs

The costs of the hydrogen network include the costs of converting the natural gas distribution network to hydrogen. This was based on annual costs figures published by National Grid ESO [93], which suggested 5.96 £m/GWh daily peak demand to do the conversion and 0.33 £m/GWh daily peak demand of annual maintenance costs.

Figure 7-2 shows the daily peak demand for hydrogen by dwelling type (from Chapter 5). This data was multiplied by the number of dwellings of each type using hydrogen boilers to calculate the daily peak hydrogen demand for each LSOA.

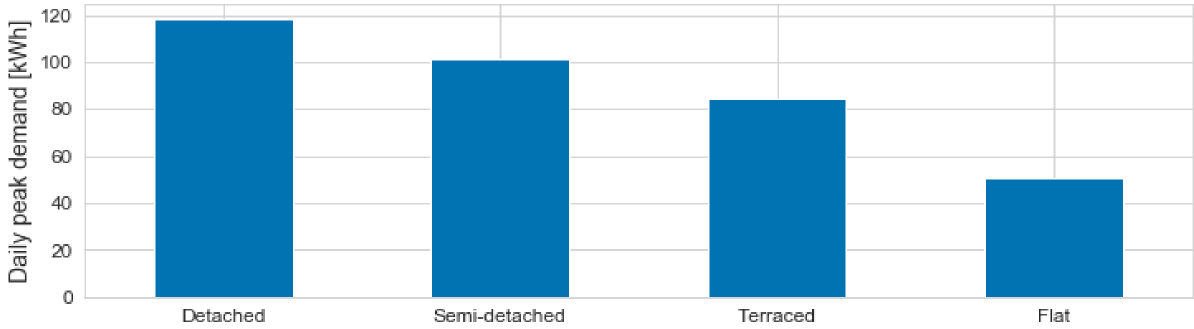


Figure 7-2: Average daily peak hydrogen demand by dwelling type for a 1-in-20 peak demand day in 2050

The costs of the electricity distribution network include the costs of reinforcing the network to cope with the additional peak electricity demand created by the electrification of heat. This was based on annual costs figures for urban area published by National Grid ESO [93], which suggested 292 £m/GW peak to build a new low voltage distribution network, 167 £/GW peak to build a new high voltage distribution network and 86 m£/GW peak demand of annual maintenance costs. These costs represent a conservative view, where the costs of reinforcing the network are equal to the costs of building a new network.

Additional peak electricity demand in the low voltage distribution network was created in some LSOAs by the uptake of electricity-based individual heating units in the two pathways. The peak electricity demand was calculated using the ADMD for each unit (shown in Figure 7-3) and the number of dwellings of each type. The ADMD of the units is based on the average daily COP at -4.2°C from Chapter 4, which was 1 for resistance heating, 2.1 for ASHPs and 2.6 for GSHPs and the average size of the units in 2050 shown in

Table 7-3.

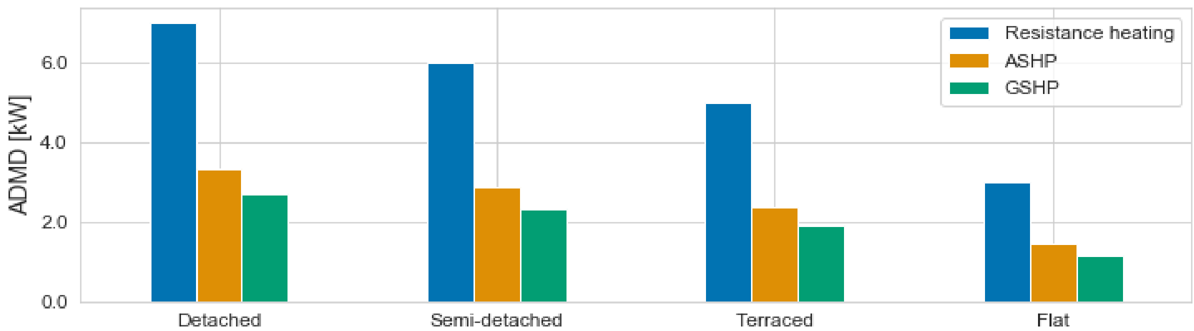


Figure 7-3: ADMD for resistance heating, ASHP and GSHP used to calculate the reinforcement costs of the electricity distribution network.

The district heating units created an additional peak electricity demand in the high voltage distribution network because it was assumed that district heating generation units were not suitable for a low voltage distribution network. Their peak electricity demand was extracted from the profiles produced in Chapter 5 for the 1-in-20 peak demand day analysis.

The costs of the heat distribution network included the construction costs of the network based on the linear heat density of the area and the length of the road. The details of this calculation are available in Chapter 6.

7.3 Energy Price Scenarios

Long-term forecasts of energy prices are frequently inaccurate. In [94], the authors showed that published oil price forecasts by the International Energy Agency had on average a 67% error on an 8-year horizon.

To overcome this issue, nine energy prices scenarios were defined, which encompass a range of possibilities. Table 7-4 shows the prices of the electricity and hydrogen chosen for each of them. These retail prices were used to calculate the operational costs related to the units included in the dwelling-side costs. The system-side costs were not impacted by the change in energy prices.

Table 7-4: Energy price scenarios for electricity and hydrogen used to compare the costs of the electrification and hydrogen pathways: (Electricity price, hydrogen price) in £/kWh.

	Hydrogen prices		
Electricity prices	Low	Medium	High
Low	(0.10, 0.10)	(0.10, 0.20)	(0.10, 0.30)
Medium	(0.20, 0.10)	(0.20, 0.20)	(0.20, 0.30)
High	(0.30, 0.10)	(0.30, 0.20)	(0.30, 0.30)

Table 7-5 shows the relationship between the way in which hydrogen is produced, and the assumed electricity and hydrogen prices. When electricity prices are lower than hydrogen prices, the hydrogen is mainly produced through electrolysis using low-carbon electricity (green hydrogen). When this is opposite, the hydrogen is mainly produced by reforming natural gas combined with a carbon capture and storage procedure (blue hydrogen). An equal price for producing electricity and hydrogen means that the hydrogen is produced with electricity and natural gas.

Table 7-5: Classification of the energy price scenarios and associated hydrogen production assumptions

Classification of energy price scenarios	Hydrogen production
Electricity prices < hydrogen prices	Hydrogen produced using low-carbon electricity (Green hydrogen)
Electricity prices > hydrogen prices	Hydrogen produced using natural gas and CCS (Blue hydrogen)
Electricity prices = hydrogen prices	A mix of Green and Blue hydrogen

My discussion of the potential green, blue hydrogen and electricity prices in 2050 will be based on this classification.

7.3.1.1 Green Hydrogen and Electricity Prices

Green hydrogen is produced through electrolysis and thus it is unlikely to have a lower price than the electricity used to produce it. In this section, the relationship between these two prices was studied, as well as other aspects of the supply chain of green hydrogen.

The CCC suggested an efficiency of 74% for electrolysers [95], and EE 69 to 95% in a report for the UK government [96]. Hence, without considering the costs of the electrolysers, the hydrogen price is expected to be 1.05 to 1.5 higher than the electricity price.

The International Renewable Energy Agency published a report on green hydrogen cost reduction, where they analysed how the change in the costs of the electrolysers could impact green hydrogen prices between 2020 and 2050 [97]. Based on their modelling, with an electricity price of 47 £/MWh[10] the green hydrogen price would decrease from 101 £/MWh in 2020 to 65 £/MWh in 2050 because of a reduction in the capital cost of electrolysers. Similarly, with an electricity price of 14 £/MWh, the green hydrogen price would decrease from 43 £/MWh in 2020 to 22 £/MWh in 2050. This is the equivalent of a hydrogen price being 1.4 to 3 times higher than the electricity price when adding the cost of electrolysers.

[10] 1 USD = 0.72 GBP conversion factor was used.

Adding the costs of transmission and distribution of hydrogen and electricity will not significantly impact these ratios. In 2020, the average network costs[11] for domestic customers represented ~45% of the gas prices and 39% of the electricity prices [98]. The transmission and distribution costs of hydrogen are not anticipated to be lower than that of natural gas [96].

Importing green hydrogen from countries with cheaper electricity may not be economically viable because EE estimated the import cost of hydrogen at 23 £/MWh - 77 £/MWh [96], without including the cost of producing hydrogen.

There are some assumptions that green hydrogen will be produced with a below-average electricity price. However, I found no literature that quantified the economic viability and barriers of such a process, which include:

- A lower load factor for the electrolysers, which would require a higher installed capacity to produce the equivalent amount of hydrogen than with electrolysers with a higher load factor;
- Competition from other technologies or services for cheap electricity such as batteries, thermal storages, demand-side response services may result in a lack of cheap electricity available for electrolysers.

It may be possible to have a green hydrogen price that is only 1.4 times higher than the electricity price or potentially slightly lower when including the costs of transmission and distribution. However, this result was based on a significant decrease in the costs of electrolysers and thus a factor of three or higher cannot be dismissed.

7.3.1.2 Blue Hydrogen and Electricity Prices

The price of blue hydrogen is based on the price of natural gas, in addition to the cost of converting natural gas to hydrogen, and capturing and storing the carbon emissions. In this section, the supply chain of blue hydrogen was studied in the same way as for green hydrogen.

To produce hydrogen using natural gas with CCS, the International Energy Agency suggested a price of 26-45 £/MWh by 2050 with a natural gas price of 4-18 £/MWh [99]. This is equivalent to hydrogen to natural gas price ratio of 1.4 to 6.5.

---

[11] Including costs to build, maintain, improve and operate the energy networks.

The security of supply is another uncertainty regarding blue hydrogen. The UK reached its peak production of natural gas in 2000, which translated into an increased amount of natural gas imports [100]. With an energy efficiency of methane reforming technologies with CCS estimated at 70 to 82% [101], a blue hydrogen scenario may increase the UK's dependency on natural gas imports.

In terms of carbon emissions, the capture rate for natural gas reforming was estimated to be around 90-95% by EE [96]. This does not include indirect emissions, which have been estimated to be around 18 to 66% of the full lifecycle emissions for natural gas by the IEA [102]. With a carbon pricing of 129 to 225 £/tCO2 in 2050 [93], the cost of the full lifecycle emissions of blue hydrogen represents an additional 7 to 10 £/MWh to the price of blue hydrogen.

An alternative option to natural gas for hydrogen production is biomethane from gasification, or anaerobic digestion of biomass. This is based on the main assumption that the agriculture sector is a net energy producer, and thus using biomethane for other sectors will not impact food production. In [103], the authors show through the example of a dairy farm that it is unlikely that agriculture could contribute significantly in providing a surplus of energy to other sectors without decreasing food production. Similar findings were shown in [104] through an assessment of the French agriculture system. Consequently, biomethane was not considered in this research.

Assuming no change in the gas price in the UK from 2020 to 2050 (~ 4 £/MWh in 2020 [105]) and based on the information described in this section, the cost to produce blue hydrogen was estimated to be between 12.6 £/MWh and 36 £/MWh (excluding transmission, distribution, and storage costs).

7.3.1.3 Electricity Prices

In the electricity projections from BEIS [105], the reference scenario as well as the low price and high price scenarios do not anticipate that the electricity price in 2035 will be lower than 200 £/MWh. This figure is near the electricity price in 2019. Other sources that modelled the GB energy system in 2050 estimated an increase of electricity price by 0 to 25% [106] [107].

7.3.1.4 Implications

Price projections of green hydrogen, blue hydrogen and electricity in the UK were made based on the current state of knowledge and analysis conducted. These are surrounded by uncertainties around factors such as the rate of development of technologies, the carbon emission reductions that can be achieved, and the availability of resources. Overall, this showed that electricity or hydrogen prices of 0.1 £/kWh were unlikely.

There are aspects to the provision of energy which are not captured by using an annual average price such as the variation in the time of use tariff. It is anticipated that in the future energy mix, large share of renewable energy sources will impact the availability of energy. There will be time where customers will be required to adapt their energy consumption to the generation. This may be translated into large variation in the time of use tariff. How the residential heating sector could be impacted by the provision of flexibility was not considered in this study. This would require estimating factors such as the amount of energy that could be shifted from one timestep to another by using a combination of building energy models with statistical information about the users and the impact of the integration of thermal storages.

7.3.2 Dwelling-side and system-side Costs of the Electrification and Hydrogen Pathways

Figure 7-4 shows the annual cost, as the sum of the dwelling-side costs and the system-side costs for Cardiff, Swansea and Newport, for each energy price scenario for the two pathways. In most scenarios, the electrification pathway appeared to be cheaper, except for the two scenarios where hydrogen price is 0.1 £/kWh and electricity prices are 0.2 and 0.3 £/kWh. The electrification pathway costs vary from 613 m£ to 906 m£, whereas the hydrogen pathways costs vary from 720 m£ to 1,444 m£. This shows a much higher sensitivity to energy prices changes from the hydrogen pathway, which is explained by the efficiency of the hydrogen boilers in comparison to HPs.

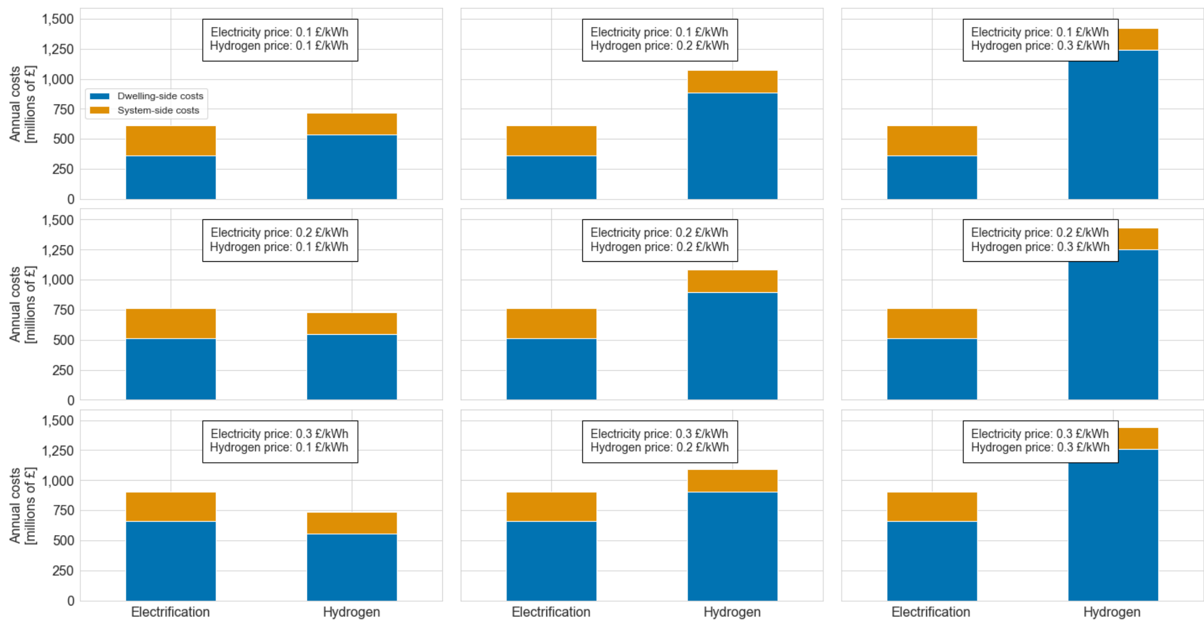


Figure 7-4: Dwelling-side and system-side costs of the electrification and hydrogen pathways for each energy price scenario.

Figure 7-5 shows the LCOH for four heating technologies, which is calculated by dividing the sum of the dwelling-side and system-side costs by the heat demand for the lowest and highest energy prices scenarios for the two pathways.

The LCOHs among the heating technologies in the electrification pathway are similar. It is around 200 £/MWh in the lowest energy price scenario and almost 300 £/MWh in the highest energy price scenario. There are wider differences between the LCOH of heating technologies and between energy price scenarios in the hydrogen pathway. The LCOH of ASHP is around 350-400 £/MWh, while the LCOH of hydrogen boiler is around 210-450 £/MWh. This shows the higher capital investment to total cost ratio of ASHPs compared to hydrogen boilers because they are less sensitive to change in energy prices then hydrogen boilers.

The higher LCOH for ASHPs in the hydrogen pathway is explained by having 70% of the ASHPs installed in flats compared to 20% in the electrification pathway. It is more expensive, in £ per kWh of heat produced, to install ASHPs in flats than in other types of dwellings and this difference is reflected in the LCOH. The differences in which type of dwellings the heating technologies were installed can also explain the difference in LCOH of the GSHPs between the two pathways.

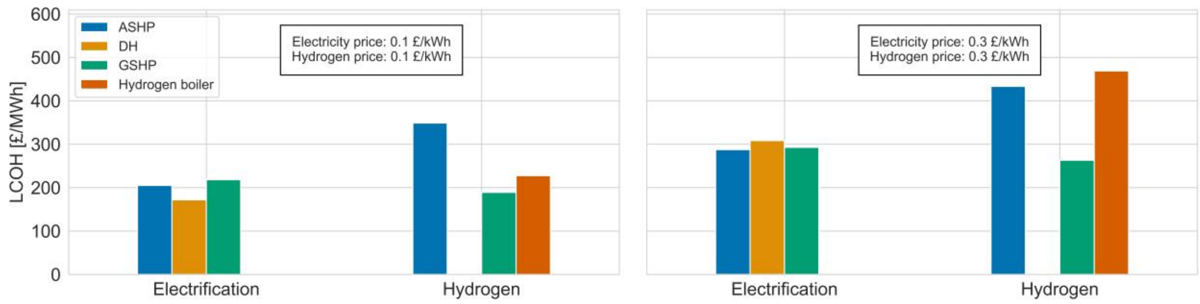


Figure 7-5: Levelised cost of heat by technology in the electrification and hydrogen pathways for two energy price scenarios.

Figure 7-6 shows the system-side costs of the two pathways. The electrification pathway costs are 30% higher than that of the hydrogen pathway. For the electrification pathway, 94% of the costs are attributed to electricity and 6% to heat network, despite the heat network supplying more than 20% of the heat demand. For the hydrogen pathways, 84% of the costs go to the conversion of the natural gas network to hydrogen and the remainder goes for the reinforcement of the electricity network.

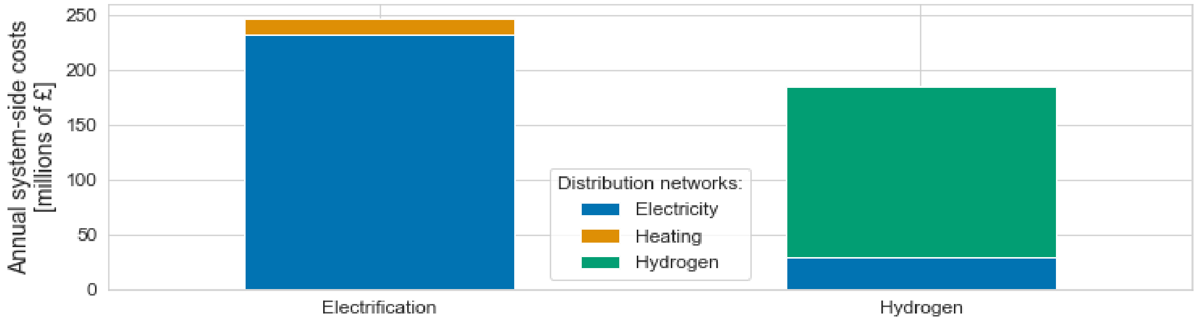


Figure 7-6: System-side costs of the electrification and hydrogen pathways

The energy price scenarios with low electricity and/or hydrogen prices were shown to be unlikely to happen, and thus they should not weigh as much as the energy price scenarios with medium to high hydrogen and electricity prices for decision-making purposes.

When analysing the energy price scenarios with medium and high energy prices surrounded by the red rectangle in Figure 7-7, The electrification pathway total costs are also consistently lower than the costs of the hydrogen pathway. The electrification pathway is also less sensitive to a change in the fuel prices. The change in absolute value when the price goes from 0.2 £/kWh to 0.3 £/kWh is lower for the electrification pathways than for the hydrogen pathway. This means that an error on the energy price projections should have less impact, positive or negative, on the electrification pathway than on the hydrogen pathway.

Figure 7-7: Dwelling-side and system-side costs of the electrification and hydrogen pathways for each energy price scenario. The question marks indicate the energy price scenarios that are unlikely to happen.

Based on the assumptions made and the results presented in this section, the heat supply options were shown to influence the sensitivity to energy prices of the two pathways. Given that future energy prices are uncertain, it is important to choose heat supply options that will minimise the consequences of errors. In the next section, the HSOA model that was described in Chapter 6 will be used to provide a more balanced approach than the electrification pathway to answer this question.

7.4 Using the Heat Supply Options Assessment Model to Identify Low Regret Options

The HSOA model from Chapter 6 was used to identify the cost-optimal heat supply options for each of the four energy price scenarios identified as most likely in the previous section (see Table 7-6). The outcomes were compared with the electrification and hydrogen pathways, before being analysed and used to identify low regrets options.

Table 7-6: Energy price scenarios for electricity and hydrogen identified as most likely and used as input to the HSOA model: (Electricity price, hydrogen price) in £/kWh.

	Hydrogen prices	
Electricity prices	Medium	High
Medium	(0.20, 0.20)	(0.20, 0.30)
High	(0.30, 0.20)	(0.30, 0.30)

7.4.1 Input Data to the Heat Supply Options Assessment Model

The same cost parameters and assumptions were taken for the HSOA model as for the electrification and hydrogen pathways, including:

- The capital and operational costs of individual heating units and district heating units.
- The reinforcement costs of the electricity distribution network and conversion costs of the natural gas network to hydrogen.
- The assumptions regarding district heating: only 80% of the heat demand was supplied through district heating in viable LSOA, the remaining 20% is supplied by individual heating technologies.
- Electric boilers, large-scale HPs and energy from waste units were the district heating supply units.
- The energy from waste units for district heating was only considered for Cardiff. The capacity installed of energy from waste units in each LSOA was capped at a

maximum of 52% of the total load. This was extracted from the installed capacity of the different units in the electrification pathway (see Chapter 4). The aggregated capacity supplied was capped at 153 MW as it was for the electrification pathway.

- The individual heating technologies considered in the HSOA model were ASHP, GSHP, hydrogen boiler and resistance heating.

7.4.2 Results from the Heat Supply Options Assessment Model and Comparison with the Electrification and Hydrogen Pathways

Figure 7-8 shows the share of the heating technologies installed in Cardiff, Swansea and Newport for the two pathways and the results of the HSOA model. Across all pathways, the average share of ASHPs is 44%. This is the only technology that appears in every pathway. The share of dwellings connected to district heating varies from 23% in the electrification pathway to 57% for the energy price scenarios with an electricity price of 0.3 £/kWh. It was not considered as an option in the hydrogen pathway. Hydrogen boilers only appear in the hydrogen pathway and were not considered as a cost-optimal option by the HSOA model. GSHPs and resistance heaters play a minimal role in all cases.

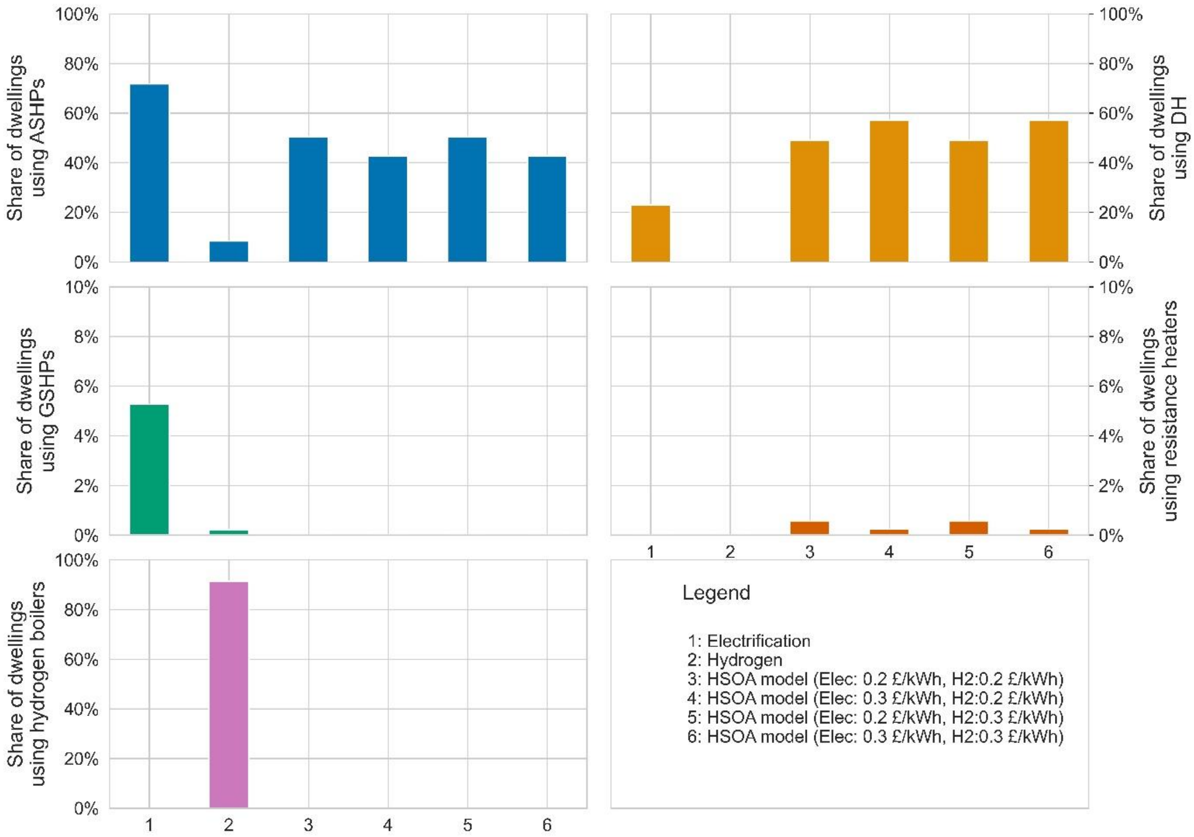


Figure 7-8: Total share of each technology installed in the Electrification, Hydrogen and HSOA modelled in Cardiff, Swansea and Newport.

More in-depth analysis of the results from the HSOA model for the four energy price scenarios was conducted for ASHPs, district heating and hydrogen boilers at local authority level to identify any potential local specificity.

7.4.2.1 Electrification of Heat Using ASHPs

Figure 7-9 shows the common number of dwellings using ASHPs (defined as the low regret option), the maximal number of dwellings using ASHPs and the dwellings that never have ASHPs installed from the results produced by the HSOA model for the four energy price scenarios.

The low regret option for ASHP entails installing ca. 64,000 (42%) units in Cardiff, ca. 54,000 (50%) in Swansea ca. 20,000 (30%) in Newport. The maximal option number in Cardiff is only higher by 1,300 units than the low regret option, whereas it is 20,000 units higher for Swansea and 6,850 for Newport. This can be explained by the low sensitivity to change of energy prices of district heating in Cardiff because of the energy from waste units.

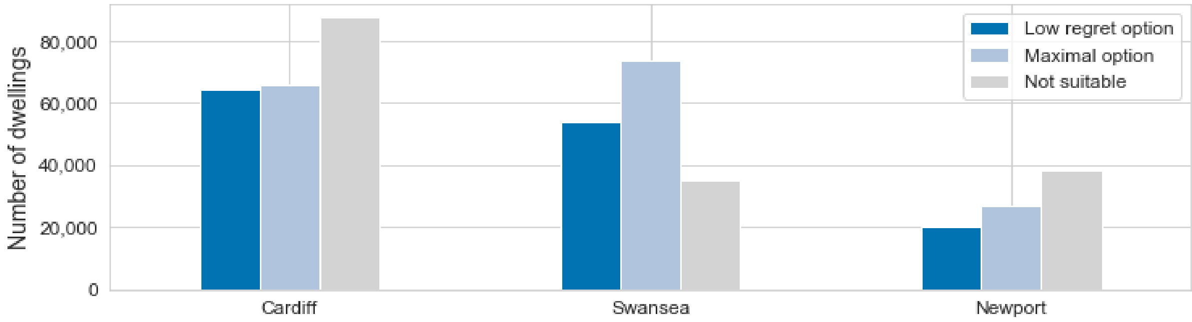


Figure 7-9: Low regret and maximal options for the number of dwellings using ASHPs in Cardiff, Swansea and Newport.

7.4.2.2 District Heating

Figure 7-10 shows the number of dwellings using district heating for the low regret and maximal options in the three local authorities. More than 87,000 (57%) are connected to district heating in Cardiff in the low regret option, ca. 34,500 (32%) in Swansea and ca. 38,000 (58%) in Newport. The high share of dwellings connected to district heating in the low regret option in Cardiff and Newport can be explained by its better economic viability in the LSOAs of these local authorities compared to the LSOAs of Swansea, as shown by the higher linear heat density of their LSOAs in Figure 7-11. The correlation between economic viability and linear heat density was shown by analysing district heating in Sweden [70].

The lower economic viability of district heating in Swansea makes them compete with other heating technologies for a lower range of energy prices, which explains the larger difference between the maximal option and the low regret option in Swansea compared to Cardiff and Newport.

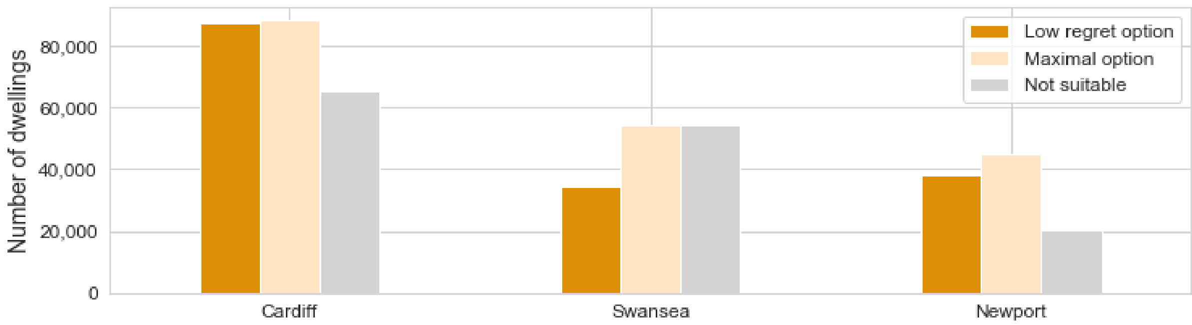


Figure 7-10: Low regret and maximal options for the number of dwellings connected to district heating in Cardiff, Swansea and Newport.

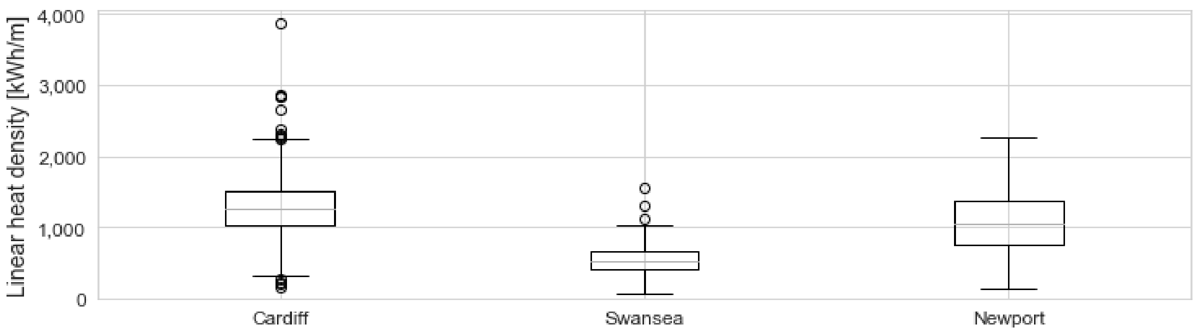


Figure 7-11: Boxplot of the linear heat density by LSOA in Cardiff, Swansea and Newport based on 2018 heat demand data.

Figure 7-12 shows the LSOAs with district heating in the electrification pathway and the most favourable pathway from the HSOA model. In the electrification pathway, 82 LSOAs over 214 were considered to be viable for district heating in Cardiff, whereas it reaches 154 in the HSOA model results.

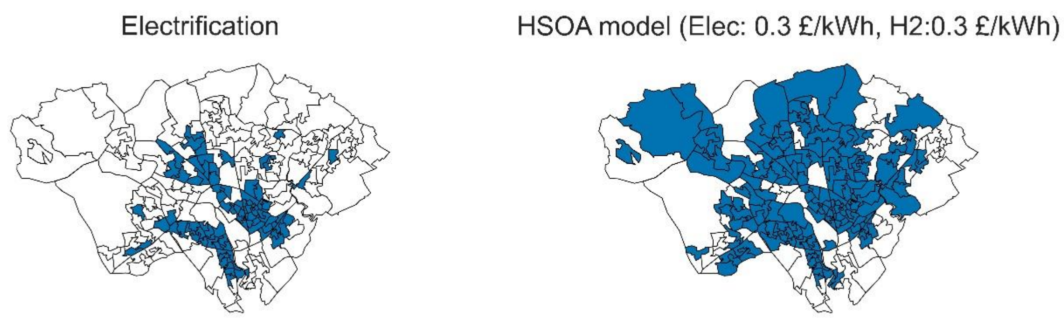


Figure 7-12: Maps of Cardiff showing the LSOAs having district heating in the Electrification pathway (left-hand panel) and the most favourable pathway for district heating from the HSOA model (right-hand panel).

In 2020, Cardiff was the only local authority with a plan to develop a district heating network [108]. This plan aimed to connect buildings with significant heat loads (e.g., County Hall, the Wales Millennium Centre, etc.) in a first phase (red line) before expanding the network in a second phase (black line). Figure 7-14 shows the LSOAs that are part of the Cardiff district heating plans.

There is no match between these LSOAs and the LSOAs in the district heating plan of Cardiff (Figure 7-12). This may be explained by the focus on non-domestic customers in the Cardiff district heating plan, which was not considered in the results of this thesis.

Nevertheless, the development of the Cardiff district heating plan may create a backbone from which domestic customers can be connected and the heat network expanded. This can be done by connecting the LSOAs with domestic customers viable for district heating that are adjacent to the LSOAs in Figure 7-14.

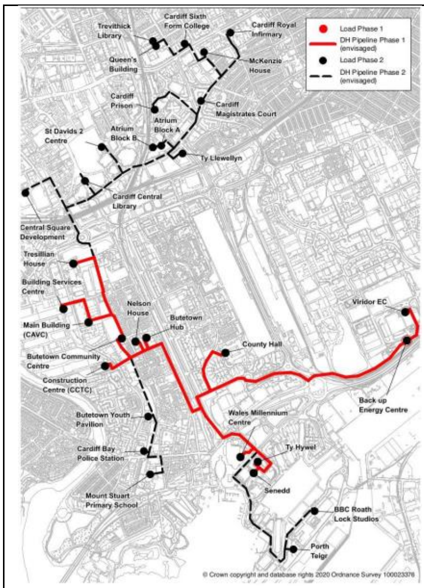


Figure 7-13: District heating plan in Cardiff [17]

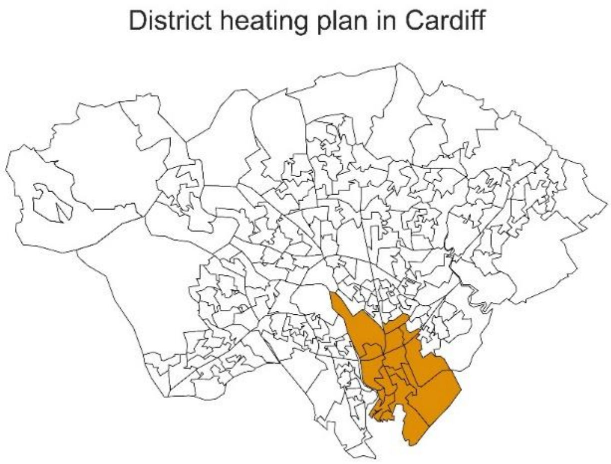


Figure 7-14: LSOAs included in the Cardiff district heating plan

Swansea and Newport do not have official plans to build district heating networks. Figure 7-15 and Figure 7-16 show the LSOAs with district heating in the electrification pathway and the most favourable pathway from the HSOA model for Swansea and Newport. It ranges from 26 to 93 for a total of 148 LSOAs in Swansea and from 23 to 82 for a total of 95 LSOAs in Newport. Identifying non-domestic heat load that can balance the domestic heat load within the most viable LSOAs could show how to develop a district heating plan in these local authorities.

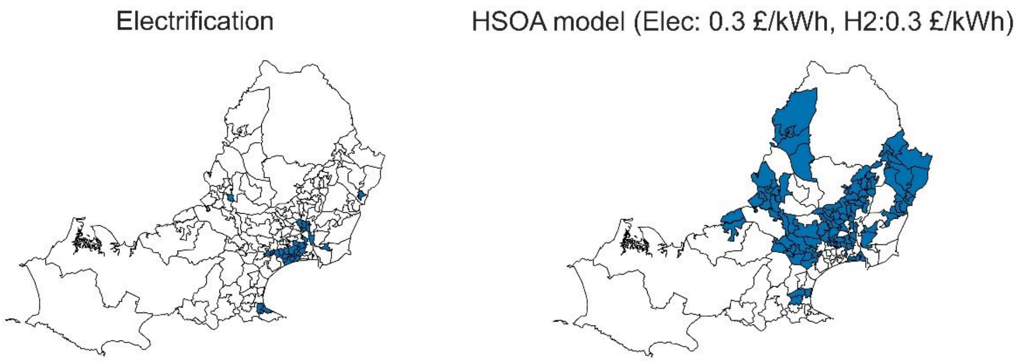


Figure 7-15: Maps of Swansea showing the LSOAs having district heating in the electrification pathway (left-hand panel) and the most favourable pathway for district heating from the HSOA model (right-hand panel).

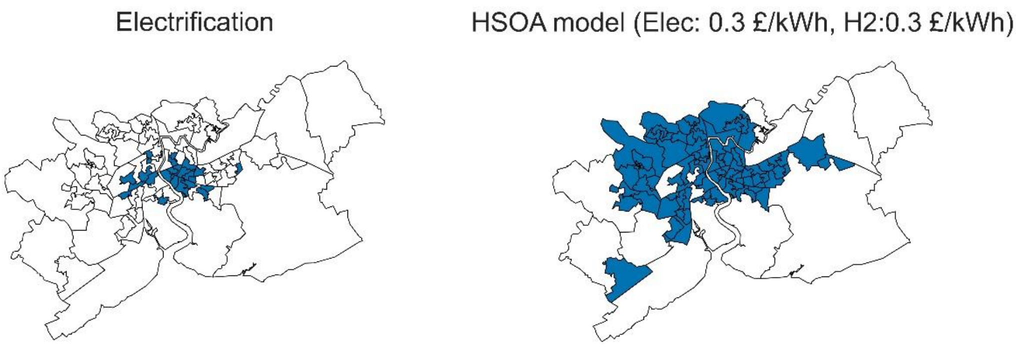


Figure 7-16: Maps of Newport showing the LSOAs having district heating in the electrification pathway (left-hand panel) and the most favourable pathway for district heating from the HSOA model (right-hand panel).

7.4.2.3 Hydrogen

Hydrogen was not identified as an option by the HSOA model in any of the four energy price scenarios.

7.4.3 Sensitivity on the capital cost of heat pumps

In addition to the fuel prices, other input data carry uncertainties which could impact the results of this study. This sensitivity analysis focused on the capital cost of heat pumps and their impacts on the results from the HSOA model. The capital investment of individual ASHPs, individual GSHPs and geothermal heat pumps for district heating were increased by 20, 50 and 100% compared to the initial cost. The HSOA model was ran with these new sets of costs.

Figure 7-17 shows the change in the the number of hydrogen boilers, ASHPs, resistance heaters installed, and number of dwellings connected to district heating chosen by the HSOA model with the increase of the capital cost of heat pumps in the four pathways. The increase in the capital cost of heat pumps is in favour of hydrogen boilers and district heating. The number of hydrogen boilers installed increases in the pathways where the hydrogen price is 0.2 £/kWh. With an increase of 100% of the capital cost of the heat pumps, hydrogen boilers supply 31% of the dwellings in the most favourable pathway (electricity price: 0.3 £/kwh and hydrogen price: 0.2 £/kWh). It remains 0% in the other pathways. The number of dwellings connected to district heating increases in all pathways and it becomes the dominant technology when the increase of the capital cost of heat pumps is over 20%. District heating supplies more than 60% of the dwellings when the increase of the capital cost of the heat pumps is 100% in all pathways. The share of individual ASHPs is dropping from more than 40% to 14% in the pathway with (electricity price: 0.3 £/kwh and hydrogen price: 0.2 £/kWh and to around 30% in the other cases.

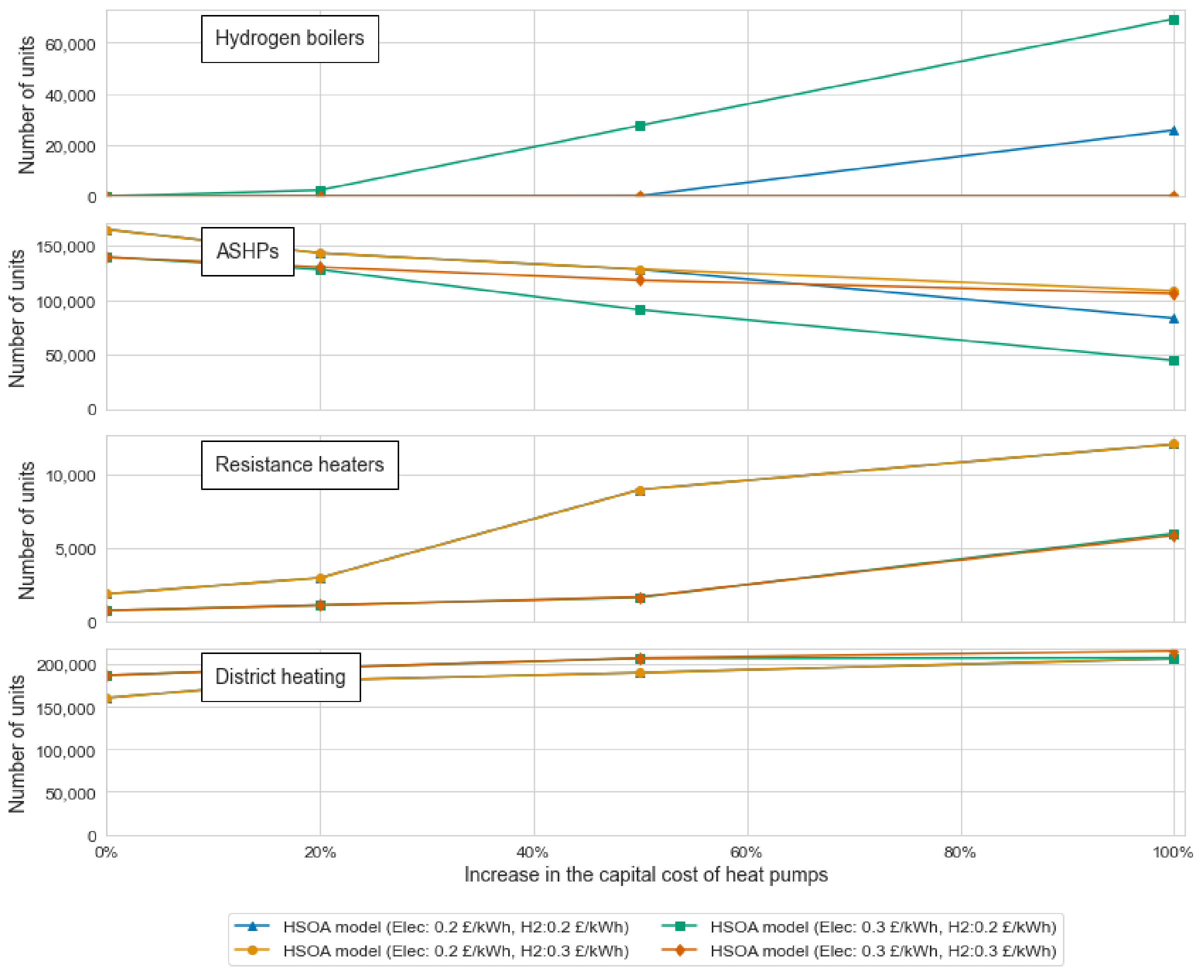


Figure 7-17: Change in the heat supply options of the four pathways for different rates of increase in the capital cost of heat pumps

Figure 7-18 shows the change in the dwelling-side and network-side costs with the increase of the capital cost of the heat pumps. The dwelling-side costs increase almost linearly across all pathways. For the network-side costs, the costs are also increasing for all the pathways except the pathway where the hydrogen price is lower than the electricity price which is decreasing. This difference can be explained by the higher share of hydrogen boilers installed in this pathway than in the others which decreases the requirements for the reinforcement of the electricity grid in favour of the conversion of the gas grid to hydrogen which is cheaper.

Overall, all the pathways see their total costs, dwelling-side costs and network side costs together, increase with the increase of the capital cost of heat pumps.

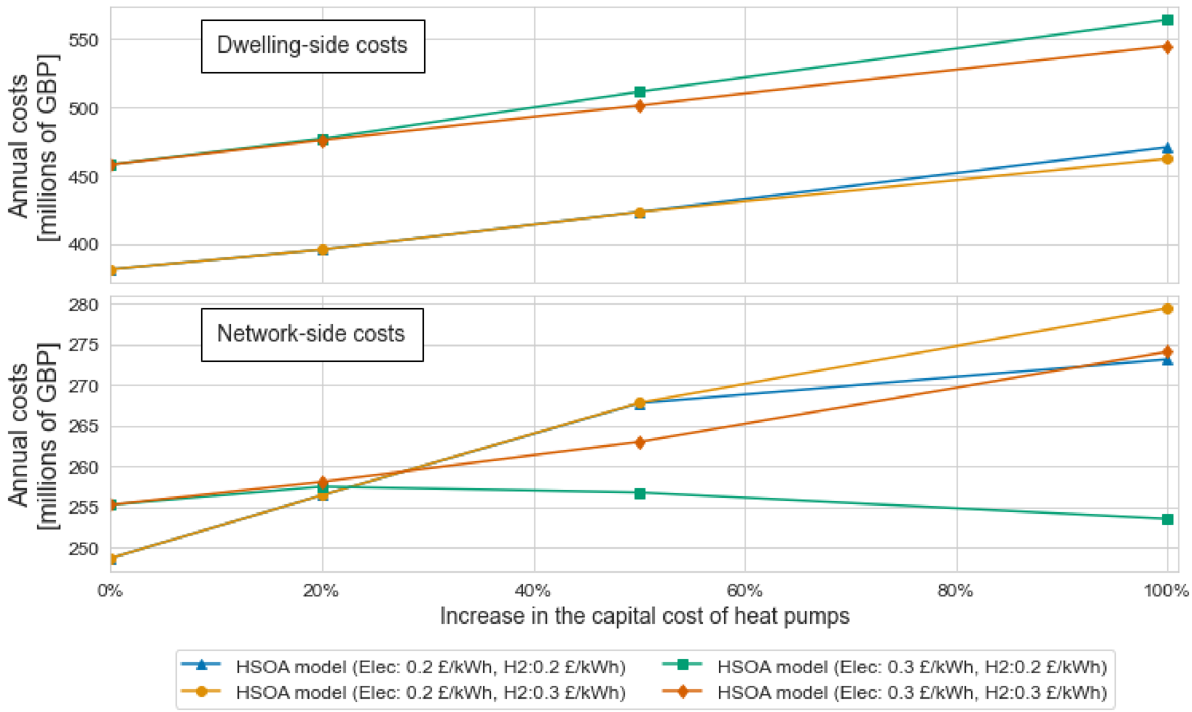


Figure 7-18: Total costs of the four pathways for different rate of increase in the capital cost of heat pumps

These results showed that district heating would benefit from an increase of the capital cost of heat pumps in all pathways. Significant increase of the capital cost of heat pumps can also favour hydrogen boilers for some specific combination of fuel prices, low hydrogen prices (0.2 £/kWh).

The increase of the capital cost of heat pumps increases the total costs of the pathways. It means that there is no other heating technology which is fully replacing the heat pumps in any of the pathways even with an increase of 100% of their capital costs.

7.5 Summary

The costs of the electrification and hydrogen pathways were calculated for nine combinations of electricity and hydrogen prices, which are called energy price scenarios. It was shown that low electricity and hydrogen prices were unlikely, and thus that energy price scenario with low electricity and hydrogen prices should not carry the same weight as others for decision making.

The study of the costs of the two heat decarbonisation pathways for the nine energy price scenarios showed that:

- The electrification pathway was cheaper than the hydrogen pathway in all energy price scenarios, except for scenarios where hydrogen price is 0.1 £/kWh and electricity price is equal to or above 0.2 £/kWh. High energy prices are favouring scenarios which do not depend on hydrogen boilers.
- The electrification pathway was less sensitive to variation in energy prices than the hydrogen pathway because of the higher energy efficiencies of the individual HPs and large-scale HPs used in district heating.
- The system-side costs of the electrification pathway were 30% higher than the hydrogen pathway. This reflects the higher capital cost associated with the electricity distribution grid than with the conversion of the natural gas grid to hydrogen.

Other heat decarbonisation pathways were built using the HSOA model for the three local authorities for the most relevant energy price scenarios. The main findings include:

- ASHPs were shown to be a low regret option for 30 to 50% of the dwellings.
- The share of district heating that was economically viable can vary from having 32% of dwellings connected to district heating in Swansea to 58% in Newport.
- Hydrogen boilers were not considered to be a viable technology by the HSOA model in the energy price scenarios.
- The current district heating plan in Cardiff did not match the results produced by the HSOA model because of its focus on non-domestic buildings.
- There are several factors that can impact the choice of heat supply options at local level such as the share of dwellings connected to the gas grid, the amount of the heat demand from each dwelling category and the linear heat density of the area.

8 Conclusions

In the literature review, it was shown that there is a lack of local heat decarbonisation strategies being developed. There are heat decarbonisation pathways available at the national level but there is no information about how these pathways would be translated to local areas – except those works done on the electrification of heat by DNOs. A major barrier identified to enable the development of local heat decarbonisation pathways was the lack of data.

In this research, the creation of data for LSOAs including annual heat demand from dwellings and heat production and energy consumption profiles of heating technologies combined with a heat supply assessment model (HSOA model) were used to develop heat decarbonisation strategies for Cardiff, Swansea and Newport.

This chapter gives (a) general conclusions to the methods and models developed in this thesis through the prism of the input data used by energy modellers, (b) discuss some uncertainties related to local heat decarbonisation strategies, (c) some policies recommendations to support heat decarbonisation and (d) some further work to improve the work done in this research.

8.1 Input Data for Energy Modellers

This PhD introduced methods that intended to fill research gaps surrounding the input data used by energy modellers when studying heat decarbonisation pathways. The contributions were a method to estimate the annual heat demand of different types of dwelling at local levels, in addition to methods were developed to synthesise half-hourly heat production and energy consumption of air-source HPs, GSHPs, resistance heaters, gas/hydrogen boilers, and district heating.

These contributions are summarised and their limitations discussed in the following sections.

8.1.1 Estimating Annual Heat Demand

A method to estimate the annual heat demand for several dwelling categories was developed. This method combined EPCs with census data to produce heat demand both before and after energy efficiency improvements at LSOA level.

The heat demand data was used to develop an understanding of the current building stock regardless of the energy used to supply the heat demand, and to build a building stock model which includes multiple dwellings categories. The lack of heat demand data in areas that are not supplied by the gas grid, and the lack of data to build detailed building stock models were problems highlighted in the literature review.

One key finding is that implementing energy efficiency measures for dwellings were estimated to have the potential to save 30% of this heat demand. This is the equivalent of bringing more than 80% of the dwelling stock to an EPC rating of C.

There are limitations to the EPC-based method due to its use of EPCs which have their own limitations including the way they are produced and the quality of the recorded data [60]. EPCs also assume a standard occupancy of the dwellings, and thus do not consider potential differences in the behaviour of people and other socio-economic factors. Furthermore, the EPC-based method does not capture the diversity of the demand within each dwelling category as it is based on averaging data and only accounts for dwellings that had an EPC. This may lead to choose sub-optimal heat supply options for some dwellings. For instance, for the dwelling with close to average heat demand an ASHP may be the optimal option but maybe a GSHP is a better option for dwellings with a larger than average heat demand.

8.1.2 Synthesising Half-hourly Heat Production and Energy Demand Profiles

Models to synthesise half-hourly heat production and energy demand profiles of ASHPs, GSHPs, resistance heaters and natural gas/hydrogen boilers were created. These models are based on XGBoost, a machine learning algorithm, and they were trained on recorded data from trial projects.

From the literature review, it was seen that a major error in modelling heat decarbonisation pathways was the use of inappropriate heat production and energy demand profiles for heating technologies. This research showed how the profiles of ASHPs, GSHPs, resistance heaters and gas boilers vary in magnitude and in time. For instance, the use of gas boiler profiles to mimic the behaviour of ASHPs would result in an overestimation of the peak energy demand by a factor higher than three.

Another key result was the production of the ADMD of ASHPs and its relation to outside air temperature which was derived from the synthesised electricity demand profiles of ASHPs. Depending at which spatial level the peak electricity demand of heat pumps needs to be calculated the value of the ADMD to be used may also change as the link between the number of units installed and the amount of diversity to be considered will vary. For example, Love et al. [45] used the heat pump datasets that also used in this research and showed that the diversity would not change significantly when more than

~200 units are considered together. However, if we look at primary substations with, for instance, less than 50 dwellings with heat pumps no diversity factor may be assumed and the ADMD would be equal to the total rated capacity of the heat pumps installed.

In addition to profiles for individual heating technologies, a method to synthesise heat and energy demand profiles for district heating that accounts for losses and thermal storage was also described. This method uses the model for GSHP to produce the shape of the heat production profiles, a daily control strategy of the thermal storage to reduce the peak of the heat demand, and a combination of screening curves and load duration curves for sizing the mix of technologies.

There are wide differences in district heating schemes because of the variation in parameters such as heat supply units, operating water temperature and type of consumers supplied thus no general conclusion were derived from these profiles.

8.2 UNCERTAINTIES IMPACTING HEAT SUPPLY OPTIONS

To build a heat decarbonisation strategy for a local area, the methodology followed in this research was to establish a baseline, define targets and assumptions, run multiple scenarios using the HSOA model and identify the heating technology which provide the lowest regrets based on the uncertainties considered.

The HSOA model was developed to assess the heat supply options for LSOAs by considering different energy price scenarios, as well as local circumstances. This model combines two sub-models: the first assesses the costs of a system based on individual heating technologies and the second assesses the costs of a system based on district heating. There is no focus on a specific heating technology in the HSOA model, which removed the bias that was noticed in some of the models listed in the literature review. It also provides an integrated approach by considering the cost of converting, reinforcing or building networks and not only the costs of the heating technologies.

Two extreme heat decarbonisation pathways were studied: the Electrification pathway assuming 100% share of electricity-based heating solutions and the Hydrogen pathway assuming a switch from gas boilers to hydrogen boilers where possible and electrification of heat otherwise.

The future fuel prices were an uncertainty that was accounted for by running the HSOA model with different configurations of electricity and hydrogen prices. The results showed that for Cardiff, Swansea and Newport the low regret option was to connect ~50% (~160,000) of the dwellings to district heating and install ASHPs in ~40% (~140,000 units) of them by 2050. A sensitivity analysis on the capital cost of heat pumps for dwellings and for district heating was also conducted. It showed that an increase of 100% of their costs, district heating would supply more than 60% of the dwellings and the heat pumps 14% in the worst-case scenario (when hydrogen prices are lower than electricity prices). District heating remains a robust heat supply options regardless of the capital cost of heat pumps.

There are other uncertainties discussed in the following that were not studied in this research but can impact the choice of heat supply options in heat decarbonisation strategies such as the constraints of the energy networks, the supply chain, the need for investment and/or regulations and the future electricity mix.

Heat pumps can be installed one by one without requiring direct changes to the electricity network decarbonising incrementally the residential heat sector. However, there will be requirements to reinforce the electricity network as their number increases and this can lead to major investment for distribution and transmission networks companies. For instance, in the Electrification pathway, the peak electricity demand increased by eighteen times between 2018 and 2050.

There is often no existing district heating network in most local areas in the UK as only 2% of the heat supplied to the residential sector was from district heating in 2018 [18]. Hence, in most local areas the construction of the district heating network will be required before connecting dwellings. This may be a time-consuming process and thus need to be accounted within a heat decarbonisation strategy. District heating will provide heat decarbonisation in a more step change manner compared to individual heating technologies.

The supply chain may bring other uncertainties to the delivery of heat decarbonisation strategies with the requirements to manufacture, install large number of units, build/reinforce/convert energy networks across the UK. The plan for the UK is to reach 600,000 heat pumps installed every year by 2028 [109]. As a point of comparison, there were 44,789 residential heat pumps approved under the domestic RHI scheme for the period from April 2014 to January 2019 [8] in the UK. Upscaling the manufacturing capabilities and the number of trained installers will be crucial to deliver heat decarbonisation.

A similar challenge can be seen to develop district heating. As seen by the low amount of heat supplied through district heating network in the UK, there is limited experience within the country and significant changes would be required to reach a share of as much 35% of the heat demand as seen in the strategy described in the Heat Roadmap Europe for UK [22].

Incentives and regulations are also keys to support the decarbonisation of heat by providing confidence to the early adopters, supply chain and decision makers. It was shown in this research that gas boilers were still the most economically viable option available based on the fuel prices of 2018 (see Chapter 6). This is not accompanied by a decarbonisation of the gas supplied or energy efficiency improvements thus there is no significant decrease of the carbon emissions in the residential heat sector. Without a change of the current incentives and regulations, there could be a higher barrier for low carbon heating technologies to enter the market which may delay the implementation of heat decarbonisation strategies.

In a future electricity mix based on a large share of fluctuating electricity sources, the fluctuation in the electricity generation will need to be managed through the provision of flexibility services or large storages.

Depending on the type of heating systems, the control of the heating systems for the end-users may be impacted by the change in the electricity mix. For electricity-based heating systems, this could mean having to shift heating hours and use the thermal inertia of the dwellings or storages (e.g., batteries or thermal storages). The cost or revenue associated with those changes may reinforce the choice for some heat supply or create opportunities for new ones to enter the market.

District heating and heat pumps were the main heat supply options chosen by the HSOA model; hydrogen boiler was not considered as a viable option. Based on the listed uncertainties of this section, there may be opportunities for hydrogen to still be a viable option in some cases when used in hydrogen boilers or within other technologies that were not considered in this research such as micro-CHP units or fuel cells. However, similar uncertainties would need to be considered for hydrogen than for district heating and heat pumps. Hydrogen based heating systems would require the conversion of the natural gas grid to hydrogen, developing the industry to produce low carbon and affordable hydrogen, changing natural gas appliances, etc. There may be advantages for hydrogen when integrating large share of fluctuating electricity sources as it may be able to provide large scale energy storage in the same way than natural gas (e.g., using large scale storage facilities and the line pack of the network). If hydrogen-based heating systems are not part of the future heat supply options for dwellings, there will be questions regarding the future of the natural gas grid including it should be decommissioned and if yes, who should bear the costs of the stranded infrastructure.

8.3 Policies to Support the Decarbonisation of the Residential Heat Sector

8.3.1 Regulations and Investment Framework for District Heating

District heating was identified as one of the most robust heating technologies to uncertainties based on the results from this research. However, its development is limited by lack of regulations and investment framework. Regulating the heat market as it is done for electricity and gas would be a first step to help with the uptake of district heating by protecting the customers and providing transparency on the pricing (Consultations are currently happening to develop these regulations [110]).

In the same way to gas and electricity networks, district heating networks are natural monopolies but different configurations could be promoted including having:

- An entity owning and managing the network as well as generating the heat, or,
- An entity owning and managing the network on one side, and heat suppliers on the other side providing heat to the network following some market rules.

The second option may provide a better incentive for the use of waste heat within district heating by providing a new revenue stream for industries. Waste heat was estimated to have the potential to cover more than 10% of the domestic heat demand of the UK [25].

In addition to regulations and defining the roles of the stakeholders in the market, district heating requires a well-defined investment framework which would help decreasing the initial capital investment. Similar to nuclear power plants in the power sector, the main cost of district heating is in the large upfront capital investment to build the infrastructure and not in its operation. Several options were discussed within a Carbon Trust report including providing a low cost of capital and the development of skills and experience to tackle this problem [111].

8.3.2 Uniformization of the Energy Tariff Structure

In the results from this research, the energy prices had a major impact in the choice of heat supply options. Providing a similar tariff structure for electricity and gas may help with the decarbonisation of heat by making electricity-based heating technologies more competitive and/or potentially drive the decarbonisation of the gas grid. In August 2021 according to Ofgem, 25.48% of the electricity bills of households was due to environmental and social obligations whereas they only account for 2.46% of the natural gas bills. These obligations were used to fund the energy transition but are mainly taken from the electricity bills and thus inflating electricity prices more than gas prices.

8.4 FURTHER WORK

8.4.1 Improved Method to Estimate the Annual Heat Demand

There are improvements to the annual heat demand that were identified which could improve the quality of the data produced. This includes enhancing the filtering process of the EPCs to remove duplicates. It would be expected to decrease the values of the estimated annual heat demand for 2018 and thus a decrease in the amount of heat demand savings when implementing energy efficiency measures.

A sensitivity analysis on the impact of changes in the annual heat demand of dwellings on the heat supply options chosen by the HSOA model would also be beneficial. A decrease in the annual heat demand may impact the viability of district heating as this would directly impact the linear heat density of the local areas. However, this could open the path to the study of the viability of low temperature district heating.

8.4.2 Estimating the Costs of Energy Efficiency Measures

The cost of energy efficiency measures was not considered in this research. It was assumed that energy efficiency measures would be implemented regardless of their costs. Calculating the cost of energy efficiency improvements for each dwelling category described in this research and constructing a cost curve for each of them could be used within an updated version of the HSOA model to estimate the threshold from which this is not viable to keep investing in energy efficiency measures instead of investing in a larger heating system.

8.4.3 The Potential for Flexibility

A future electricity mix based on larger share of renewable energy may require for the residential heat sector to provide flexibility to the power system. Using a combination of the half-hourly heat production and energy demand profiles produced in this research combined with building physics models could help estimate the amount of flexibility available at each time step and assess if this could impact the choice of heat supply options.

This could also highlight the differences in the heat production and energy demand profiles of heating technologies in different type of dwellings. In this research, it was considered that the same heating technology would be used in the same way regardless of the type of dwellings in which it is installed. This would need further investigation.

8.4.4 Producing Cooling Demand Data

Currently, the cooling demand in the UK is unmet demand as most dwellings do not own cooling appliances. However, this may change with the effect of climate change on the temperature during summertime. The cooling demand could be estimated by combining weather projections with knowledge about the envelope of the dwellings (i.e., the losses of the dwellings estimated from the annual heat demand data). Depending on how significant the cooling demand is there may be an opportunity to upgrade the HSOA model to include it and analyse how this could impact the choice of heat supply options.

9 References

[1] Office for National Statistics, “2011 Census,” 2011. Accessed: Aug. 23, 2019. [Online]. Available: https://www.ons.gov.uk/census/2011census

[2] J. Palmer and I. Cooper, “Great Britain’s housing energy fact file 2011,” Department of Energy & Climate Change, 2011. Accessed: Mar. 12, 2021. [Online]. Available: https://www.gov.uk/government/publications/great-britains-housing-energy-fact-file-2011

[3] Department for Business, Energy & Industrial Strategy, “Sub-national electricity and gas consumption summary report 2018,” Department for Business, Energy & Industrial Strategy, 2018. Accessed: Dec. 01, 2019. [Online]. Available: https://www.gov.uk/government/statistics/sub-national-electricity-and-gas-consumption-summary-report-2016

[4] Department for Business, Energy & Industrial Strategy, “Energy Consumption in the UK (ECUK) 2019 Data Tables,” Department for Business, Energy & Industrial Strategy, 2019. [Online]. Available: https://www.gov.uk/government/statistics/energy-consumption-in-the-uk

[5] Cooper, Ian and Palmer, Jason, “United Kingdom housing energy fact file: 2013,” Department of Energy & Climate Change, 2013. Accessed: Mar. 12, 2021. [Online]. Available: https://www.gov.uk/government/statistics/united-kingdom-housing-energy-fact-file-2013

[6] Department for Business, Energy & Industrial Strategy, “English Housing Survey 2018: energy report,” Department for Business, Energy & Industrial Strategy, 2018. Accessed: Mar. 12, 2021. [Online]. Available: https://www.gov.uk/government/statistics/english-housing-survey-2018-energy-report

[7] P. S. Mallaburn and N. Eyre, “Lessons from energy efficiency policy and programmesin the UK from 1973 to 2013,” *Energy Effic.*, vol. 7, no. 1, pp. 23–41, Feb. 2014, doi: 10.1007/s12053-013-9197-7.

[8] “Public reports and data: Domestic RHI,” *Ofgem.gov.uk*, Jun. 07, 2016. https://www.ofgem.gov.uk/environmental-programmes/domestic-rhi/contacts-guidance-and-resources/public-reports-and-data-domestic-rhi (accessed Apr. 12, 2018).

[9] “Conversion factors 2017 - Full set (for advanced users),” Department for Business, Energy & Industrial Strategy, 2017. Accessed: Jan. 18, 2018. [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/635633/Conversion_factors_2017_-_Full_set__for_advanced_users__v02-00.xls

[10] “Sixth Carbon Budget,” *Climate Change Committee*. https://www.theccc.org.uk/publication/sixth-carbon-budget/ (accessed Mar. 10, 2021).

[11] “Historical electricity data,” *GOV.UK*. https://www.gov.uk/government/statistical-data-sets/historical-electricity-data (accessed Mar. 13, 2021).

[12] “Net Zero-The UK’s contribution to stopping global warming,” Committee on Climate Change, May 2019. Accessed: May 13, 2019. [Online]. Available: https://www.theccc.org.uk/wp-content/uploads/2019/05/Net-Zero-The-UKs-contribution-to-stopping-global-warming.pdf

[13] “Carbon Footprint of Heat Generation,” Houses of Parliament Parliamentiary Office Of Science and Technology, May 2016. Accessed: Jan. 18, 2018. [Online]. Available: http://researchbriefings.files.parliament.uk/documents/POST-PN-0523/POST-PN-0523.pdf

[14] A. Canet, M. Qadrdan, and N. Jenkins, “Heat demand mapping and assessment of heat supply options for local areas – The case study of Neath Port Talbot,” *Energy*, vol. 217, p. 119298, Feb. 2021, doi: 10.1016/j.energy.2020.119298.

[15] D. for B. E. & I. Strategy (BEIS) and C. Skidmore, “UK becomes first major economy to pass net zero emissions law,” 06-27 2019.
[16] M. Chaudry, M. Abeysekera, S. H. R. Hosseini, N. Jenkins, and J. Wu, “Uncertainties in decarbonising heat in the UK,” *Energy Policy*, vol. 87, pp. 623–640, Dec. 2015, doi: 10.1016/j.enpol.2015.07.019.
[17] “2050 Pathways for Domestic Heat,” Delta Energy & Environment, 2012. Accessed: Jan. 29, 2018. [Online]. Available: http://www.energynetworks.org/assets/files/gas/futures/Delta-ee_ENA%20Final%20Report%20OCT.pdf.pdf
[18] National Grid ESO, “FES 2020 documents,” National Grid ESO, 2020. Accessed: Feb. 26, 2021. [Online]. Available: https://www.nationalgrideso.com/future-energy/future-energy-scenarios/fes-2020-documents
[19] “Development of trajectories for residential heat decarbonisation to inform the Sixth Carbon Budget (Element Energy),” The Climate Change Committee (CCC). Accessed: Feb. 26, 2021. [Online]. Available: https://www.theccc.org.uk/publication/development-of-trajectories-for-residential-heat-decarbonisation-to-inform-the-sixth-carbon-budget-element-energy/
[20] G. Strbac *et al.*, “Analysis of alternative UK heat decarbonisation pathways,” Imperial College London, Jun. 2018. Accessed: Nov. 30, 2018. [Online]. Available: https://www.theccc.org.uk/publication/analysis-of-alternative-uk-heat-decarbonisation-pathways/
[21] Committee on Climate Change, “Next-steps-for-UK-heat-policy-Committee-on-Climate-Change-October-2016.pdf.” https://www.theccc.org.uk/wp-content/uploads/2016/10/Next-steps-for-UK-heat-policy-Committee-on-Climate-Change-October-2016.pdf (accessed Dec. 06, 2017).
[22] S. Paardekooper *et al.*, “Heat Roadmap United Kingdom : Quantifying the Impact of Low-Carbon Heating and Cooling Roadmaps,” Oct. 2018, Accessed: Nov. 30, 2018. [Online]. Available: http://vbn.aau.dk/en/publications/heat-roadmap-united-kingdom--quantifying-the-impact-of-lowcarbon-heating-and-cooling-roadmaps(97ba1469-8cb8-40fd-b0ed-3f2d25c866f7).html
[23] Mathiesen, B. V., “Heat Roadmap Europe Democratizising knowledge bottom up and top down, Key findings and recommendations for decarbonising H&C Sector,” Oct. 17, 2018.
[24] F. Jalil-Vega and A. D. Hawkes, “Spatially resolved model for studying decarbonisation pathways for heat supply and infrastructure trade-offs,” *Appl. Energy*, vol. 210, pp. 1051–1072, Jan. 2018, doi: 10.1016/j.apenergy.2017.05.091.
[25] “The potential for recovering and using surplus heat from industry,” Element energy for DECC, 2014. Accessed: May 31, 2018. [Online]. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/294900/element_energy_et_al_potential_for_recovering_and_using_surplus_heat_from_industry.pdf
[26] C. Calderón, C. Underwood, J. Yi, A. Mcloughlin, and B. Williams, “An area-based modelling approach for planning heating electrification,” *Energy Policy*, vol. 131, pp. 262–280, Aug. 2019, doi: 10.1016/j.enpol.2019.04.023.
[27] Western Power Distribution, “Distribution Future Energy Scenarios A generation and demand study Technology growth scenarios to 2032,” Western Power Distribution, Jun. 2018. Accessed: Oct. 28, 2021. [Online]. Available: https://www.westernpower.co.uk/downloads/6710
[28] “Future Wales: The National Plan 2040,” Welsh government, Feb. 2021. Accessed: Feb. 28, 2021. [Online]. Available: https://gov.wales/future-wales-national-plan-2040-0

[29] "Heat networks pipeline," *GOV.UK*. https://www.gov.uk/government/publications/hndu-pipeline (accessed Mar. 07, 2021).
[30] S. D. Watson, K. J. Lomas, and R. A. Buswell, "Decarbonising domestic heating: What is the peak GB demand?," *Energy Policy*, vol. 126, pp. 533–544, Mar. 2019, doi: 10.1016/j.enpol.2018.11.001.
[31] F. Jalil-Vega and A. D. Hawkes, "The effect of spatial resolution on outcomes from energy systems modelling of heat decarbonisation," *Energy*, vol. 155, pp. 339–350, Jul. 2018, doi: 10.1016/j.energy.2018.04.160.
[32] Department for Business, Energy & Industrial Strategy, "Lower and Middle Super Output Areas gas consumption," Department for Business, Energy & Industrial Strategy. Accessed: Aug. 16, 2019. [Online]. Available: https://www.gov.uk/government/statistics/lower-and-middle-super-output-areas-gas-consumption
[33] P. I. Knight, H. Iorwerth, and D. S. Lannon, "Re-Energising Wales Project Work Package 1 – Half-Hourly Energy Demand Profiles For Wales For 2016," p. 55.
[34] "AddressBase premium," Ordnance Survey, Wales, 2017. Accessed: Aug. 23, 2019. [Online]. Available: https://www.ordnancesurvey.co.uk/business-and-government/products/addressbase-products.html
[35] B. Möller, E. Wiechers, U. Persson, L. Grundahl, and D. Connolly, "Heat Roadmap Europe: Identifying local heat demand and supply areas with a European thermal atlas," *Energy*, vol. 158, pp. 281–292, Sep. 2018, doi: 10.1016/j.energy.2018.06.025.
[36] "Managing the future network impact of electrification of heat," Delta Energy & Environment, Jun. 2016.
[37] E. McKenna and M. Thomson, "High-resolution stochastic integrated thermal-electrical domestic demand model," *Appl. Energy*, vol. 165, pp. 445–461, Mar. 2016, doi: 10.1016/j.apenergy.2015.12.089.
[38] D. Fischer, T. Wolf, J. Scherer, and B. Wille-Haussmann, "A stochastic bottom-up model for space heating and domestic hot water load profiles for German households," *Energy Build.*, vol. 124, pp. 120–128, Jul. 2016, doi: 10.1016/j.enbuild.2016.04.069.
[39] O. Ruhnau, L. Hirth, and A. Praktiknjo, "Time series of heat demand and heat pump efficiency for energy system modeling," *Sci. Data*, vol. 6, no. 1, p. 189, Oct. 2019, doi: 10.1038/s41597-019-0199-y.
[40] R. Sansom, "Decarbonising low grade heat for low carbon future," Nov. 2014, Accessed: Jan. 16, 2018. [Online]. Available: http://spiral.imperial.ac.uk/handle/10044/1/25503
[41] D. Quiggin and R. Buswell, "The implications of heat electrification on national electrical supply-demand balance under published 2050 energy scenarios," *Energy*, vol. 98, pp. 253–270, Mar. 2016, doi: 10.1016/j.energy.2015.11.060.
[42] M. Bourdeau, X. qiang Zhai, E. Nefzaoui, X. Guo, and P. Chatellier, "Modeling and forecasting building energy consumption: A review of data-driven techniques," *Sustain. Cities Soc.*, vol. 48, p. 101533, Jul. 2019, doi: 10.1016/j.scs.2019.101533.
[43] D. P. Jenkins, S. Patidar, and S. A. Simpson, "Synthesising electrical demand profiles for UK dwellings," *Energy Build.*, vol. 76, pp. 605–614, Jun. 2014, doi: 10.1016/j.enbuild.2014.03.012.
[44] Z. Wang, J. Crawley, F. G. N. Li, and R. Lowe, "Sizing of district heating systems based on smart meter data: Quantifying the aggregated domestic energy demand and demand diversity in the UK," *Energy*, vol. 193, p. 116780, Feb. 2020, doi: 10.1016/j.energy.2019.116780.
[45] J. Love *et al.*, "The addition of heat pump electricity load profiles to GB electricity demand: Evidence from a heat pump field trial," *Appl. Energy*, vol. 204, no. Supplement C, pp. 332–342, Oct. 2017, doi: 10.1016/j.apenergy.2017.07.026.

[46] P. E. Dodds, “Integrating housing stock and energy system models as a strategy to improve heat decarbonisation assessments,” *Appl. Energy*, vol. 132, pp. 358–369, Nov. 2014, doi: 10.1016/j.apenergy.2014.06.079.
[47] D. Scamman *et al.*, “Heat Decarbonisation Modelling Approaches in the UK: An Energy System Architecture Perspective,” *Energies*, vol. 13, no. 8, Art. no. 8, Jan. 2020, doi: 10.3390/en13081869.
[48] E. Popovski, T. Fleiter, H. Santos, V. Leal, and E. O. Fernandes, “Technical and economic feasibility of sustainable heating and cooling supply options in southern European municipalities-A case study for Matosinhos, Portugal,” *Energy*, vol. 153, pp. 311–323, Jun. 2018, doi: 10.1016/j.energy.2018.04.036.
[49] S. Ben Amer-Allam, M. Münster, and S. Petrović, “Scenarios for sustainable heat supply and heat savings in municipalities - The case of Helsingør, Denmark,” *Energy*, vol. 137, pp. 1252–1263, Oct. 2017, doi: 10.1016/j.energy.2017.06.091.
[50] E. Popovski, A. Aydemir, T. Fleiter, D. Bellstädt, R. Büchele, and J. Steinbach, “The role and costs of large-scale heat pumps in decarbonising existing district heating networks – A case study for the city of Herten in Germany,” *Energy*, vol. 180, pp. 918–933, Aug. 2019, doi: 10.1016/j.energy.2019.05.122.
[51] B. Möller, E. Wiechers, U. Persson, L. Grundahl, R. S. Lund, and B. V. Mathiesen, “Heat Roadmap Europe: Towards EU-Wide, local heat supply strategies,” *Energy*, vol. 177, pp. 554–564, Jun. 2019, doi: 10.1016/j.energy.2019.04.098.
[52] Ministry of Housing, Communities and Local Government, “Domestic Energy Performance Certificate Register,” *EPC register*, Nov. 13, 2020. www.epcregister.com (accessed Nov. 13, 2020).
[53] Office for National Statistics, “Postcode to Output Area to Lower Layer Super Output Area to Middle Layer Super Output Area to Local Authority District (February 2018) Lookup in the UK,” Jun. 30, 2018. https://data.gov.uk/dataset/9b090605-9861-4bb4-9fa4-6845daa2de9b/postcode-to-output-area-to-lower-layer-super-output-area-to-middle-layer-super-output-area-to-local-authority-district-february-2018-lookup-in-the-uk (accessed Aug. 26, 2021).
[54] StatsWales, “Dwelling stock estimates by local authority and tenure,” 2019. https://statswales.gov.wales/Catalogue/Housing/Dwelling-Stock-Estimates/dwellingstockestimates-by-localauthority-tenure (accessed Nov. 06, 2020).
[55] Centre for Sustainable Energy, “Beyond average consumption - Development of a framework for assessing impact of policy proposals on different consumer groups,” Centre for sustainable energy, Mar. 2014. Accessed: Aug. 16, 2019. [Online]. Available: https://www.cse.org.uk/downloads/reports-and-publications/policy/beyond_average_consumption_update_2014.pdf
[56] Department for Business, Energy & Industrial Strategy, “Energy Consumption in the UK (ECUK) 2017 Data Tables,” Department for Business, Energy & Industrial Strategy, 2017.
[57] Delta Energy & Environment, “Electrification of Heat and the Impact on the Scottish Electricity System,” Delta Energy & Environment, Mar. 2016. [Online]. Available: https://www.climatexchange.org.uk/media/1897/electrification_of_heat_and_impact_on_scottish_electricity_system_-_final_report1.pdf
[58] Department of Energy & Climate Change, “Sub-national consumption statistics - Methodology and Guidance booklet,” Department of Energy & Climate Change, Sep. 2014.
[59] Department of Energy and Climate Change, “Overview of weather correction of gas industry consumption data,” Department of Energy & Climate Change, Mar. 2014. Accessed: Oct. 18, 2021. [Online]. Available:

https://www.gov.uk/government/publications/overview-of-weather-correction-of-gas-industry-consumption-data
[60] O. Pasichnyi, J. Wallin, F. Levihn, H. Shahrokni, and O. Kordas, “Energy performance certificates — New opportunities for data-enabled urban energy policy instruments?,” *Energy Policy*, vol. 127, pp. 486–499, Apr. 2019, doi: 10.1016/j.enpol.2018.11.051.
[61] T. Chen and C. Guestrin, “XGBoost: A Scalable Tree Boosting System,” in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco, California, USA, Aug. 2016, pp. 785–794. doi: 10.1145/2939672.2939785.
[62] “Renewable Heat Premium Payment Scheme: Heat Pump Monitoring: Cleaned Data, 2013-2015,” UK Data Service. Accessed: Jan. 16, 2018. [Online]. Available: http://doi.org/10.5255/UKDA-SN-8151-1
[63] AECOM Building Engineering, “Energy Demand Research Project: Early Smart Meter Trials, 2007-2010,” UK Data Service, 2014. [Online]. Available: http://doi.org/10.5255/UKDA-SN-7591-1
[64] “Temperature | BMRS,” *Elexon*, 2018. https://www.bmreports.com/bmrs/?q=generation/tempraturedata (accessed Jan. 26, 2018).
[65] K. Le, M. Huang, and N. Hewitt, “Domestic High Temperature Air Source Heat Pump: Performance Analysis Using TRNSYS Simulations,” *5th Int. High Perform. Build. Conf. Purdue*, Jul. 2018, Accessed: Jan. 15, 2020. [Online]. Available: https://pure.ulster.ac.uk/en/publications/domestic-high-temperature-air-source-heat-pump-performance-analys
[66] M. Gibson, “Microgeneration Installation Standard: MIS 3005,” Department of Energy & Climate Change, 2013.
[67] “Module 36: Air source heat pumps,” *CIBSE Journal*. https://www.cibsejournal.com/cpd/modules/2012-01/ (accessed Apr. 05, 2020).
[68] J. Kissock, J. Haberl, and D. Claridge, “Inverse modeling toolkit: Numerical algorithms,” *ASHRAE Trans.*, vol. 109, pp. 425–434, Jan. 2003.
[69] “Module 149: Effective control for condensing gas boiler systems,” *CIBSE Journal*. https://www.cibsejournal.com/cpd/modules/2019-07-gas/ (accessed Apr. 05, 2020).
[70] S. Frederiksen and S. Werner, *District Heating and Cooling*. Studentlitteratur AB, 2013. [Online]. Available: https://books.google.co.uk/books?id=vH5zngEACAAJ
[71] “Technology Data for Energy Plants for Electricity and District heating generation,” Energinet and Danish Energy Agency, Aug. 2016. Accessed: Aug. 21, 2019. [Online]. Available: https://ens.dk/sites/ens.dk/files/Analyser/technology_data_catalogue_for_el_and_dh_-_aug_2016_upd_oct18.pdf
[72] Department for Business, Energy & Industrial Strategy, “Regional and local authority gas consumption statistics,” *GOV.UK*, May 12, 2020. https://www.gov.uk/government/statistical-data-sets/gas-sales-and-numbers-of-customers-by-region-and-local-authority (accessed Dec. 05, 2020).
[73] “UK housing: Fit for the future?,” Committee on Climate Change, Feb. 2019. Accessed: Dec. 05, 2020. [Online]. Available: https://www.theccc.org.uk/publication/uk-housing-fit-for-the-future/
[74] “Measurement of Domestic Hot Water Consumption in Dwellings,” Energy Saving trust.
[75] “Large scale heat pumps in Europe,” European heat pump association.
[76] M. (327173) Jones, “Framework for Design & Planning of LV Housing Developments, including U/G Networks and Associated HV/LV S/S,” SP Energy Networks.
[77] R. Nickerson, “Gas Demand Forecasting Methodology,” National Grid, Nov. 2016.

[78] “Data explorer | National Grid ESO.” https://demandforecast.nationalgrid.com/efs_demand_forecast/faces/DataExplorer;jsessionid=RYNgwEMxdUvR88fBTkS-DKin3XDopWsgfCFhi-Lmlw12fStlod-d!415586445 (accessed Oct. 25, 2020).
[79] Christian Barteczko-Hibbert, “After Diversity Maximum Demand Insight Report,” Customer-Led Network Revolution, Feb. 2015.
[80] U. Persson and S. Werner, “Heat distribution and the future competitiveness of district heating,” *Appl. Energy*, vol. 88, no. 3, pp. 568–576, Mar. 2011, doi: 10.1016/j.apenergy.2010.09.020.
[81] Ordnance Survey, “OS Open Roads | High Level View of Roads | Vector Map Data | Free Download.” https://www.ordnancesurvey.co.uk/business-government/products/open-map-roads (accessed Sep. 01, 2021).
[82] “Technology Data for Energy Transport,” Energinet and Danish Energy Agency, Dec. 2017. Accessed: Nov. 21, 2018. [Online]. Available: https://ens.dk/sites/ens.dk/files/Analyser/technology_data_for_energy_transport_dec_2017_1.pdf
[83] J. Cox, “The Potential and Costs of District Heating Networks,” p. 152, 2009.
[84] W. E. Hart *et al.*, *Pyomo-optimization modeling in python*, Second., vol. 67. Springer Science & Business Media, 2017.
[85] W. E. Hart, J.-P. Watson, and D. L. Woodruff, “Pyomo: modeling and solving mathematical programs in Python,” *Math. Program. Comput.*, vol. 3, no. 3, pp. 219–260, 2011.
[86] “Energy Performance of Buildings Data England and Wales,” Ministry of Housing, Communities and Local Government. Accessed: Aug. 23, 2019. [Online]. Available: https://epc.opendatacommunities.org/login
[87] “Updated energy and emissions projections: 2017,” *GOV.UK*. https://www.gov.uk/government/publications/updated-energy-and-emissions-projections-2017 (accessed Aug. 01, 2019).
[88] “Fuel prices and Carbon factors,” *Energy Saving Trust*, 2018. https://www.energysavingtrust.org.uk/about-us/our-calculations (accessed Oct. 02, 2019).
[89] O. Eriksson and G. Finnveden, “Energy Recovery from Waste Incineration—The Importance of Technology Data and System Boundaries on CO2 Emissions,” *Energies*, vol. 10, no. 4, Art. no. 4, Apr. 2017, doi: 10.3390/en10040539.
[90] “Technology Data for Individual Heating Installations,” Energinet and Danish Energy Agency, Mar. 2018.
[91] “Cost of installing heating measures in domestic properties,” Department for Business, Energy & Industrial Strategy, Jan. 2020. Accessed: Apr. 26, 2021. [Online]. Available: https://www.gov.uk/government/publications/cost-of-installing-heating-measures-in-domestic-properties
[92] “Combi Boilers Guide: Costs, Savings, And benefits | OVO Energy.” https://www.ovoenergy.com/guides/energy-guides/combi-boiler-prices-and-savings-explained.html, https://www.ovoenergy.com/guides/energy-guides/combi-boiler-prices-and-savings-explained.html (accessed Apr. 26, 2021).
[93] “Future Energy Scenarios 2020 Costing Data Workbook,” National Grid ESO, Jan. 2020. [Online]. Available: https://www.nationalgrideso.com/news/analysing-costs-our-future-energy-scenarios
[94] H. Wachtmeister, P. Henke, and M. Höök, “Oil projections in retrospect: Revisions, accuracy and current uncertainty,” *Appl. Energy*, vol. 220, pp. 138–153, Jun. 2018, doi: 10.1016/j.apenergy.2018.03.013.
[95] “Hydrogen in a low-carbon economy,” Committee on Climate Change, Nov. 2018. Accessed: Feb. 12, 2021. [Online]. Available: https://www.theccc.org.uk/publication/hydrogen-in-a-low-carbon-economy/

[96] "Hydrogen supply chain evidence base," Department for Business, Energy & Industrial Strategy, Nov. 2018. Accessed: Feb. 12, 2021. [Online]. Available: https://www.gov.uk/government/publications/hydrogen-supply-chain-evidence-base
[97] "Green hydrogen cost reduction," International renewable energy agency, Dec. 2020. Accessed: Feb. 12, 2021. [Online]. Available: /publications/2020/Dec/Green-hydrogen-cost-reduction
[98] "Understand your gas and electricity bills," *Ofgem*, Jun. 19, 2013. https://www.ofgem.gov.uk/consumers/household-gas-and-electricity-guide/understand-your-gas-and-electricity-bills (accessed Mar. 15, 2021).
[99] "Global average levelised cost of hydrogen production by energy source and technology, 2019 and 2050 – Charts – Data & Statistics," *IEA*. https://www.iea.org/data-and-statistics/charts/global-average-levelised-cost-of-hydrogen-production-by-energy-source-and-technology-2019-and-2050 (accessed Feb. 12, 2021).
[100] "Digest of UK Energy Statistics (DUKES): natural gas," Department for Business, Energy & Industrial Strategy, Jul. 2020. Accessed: Feb. 12, 2021. [Online]. Available: https://www.gov.uk/government/statistics/natural-gas-chapter-4-digest-of-united-kingdom-energy-statistics-dukes
[101] "Future energy scenarios," National Grid ESO, Jul. 2019. Accessed: Sep. 30, 2019. [Online]. Available: http://fes.nationalgrid.com/media/1409/fes-2019.pdf
[102] "Methane Tracker 2020 – Analysis," *IEA*. https://www.iea.org/reports/methane-tracker-2020 (accessed Feb. 13, 2021).
[103] M. V. Markussen, S. Pugesgaard, P. Oleskowicz-Popiel, J. E. Schmidt, and H. Østergård, "Net-Energy Analysis of Integrated Food and Bioenergy Systems Exemplified by a Model of a Self-Sufficient System of Dairy Farms," *Front. Energy Res.*, vol. 3, 2015, doi: 10.3389/fenrg.2015.00049.
[104] S. Harchaoui and P. Chatzimpiros, "Can Agriculture Balance Its Energy Consumption and Continue to Produce Food? A Framework for Assessing Energy Neutrality Applied to French Agriculture," *Sustainability*, vol. 10, no. 12, p. 4624, Dec. 2018, doi: 10.3390/su10124624.
[105] "Updated energy and emissions projections: 2018," *GOV.UK*. https://www.gov.uk/government/publications/updated-energy-and-emissions-projections-2018 (accessed Feb. 12, 2021).
[106] J. Price, M. Zeyringer, D. Konadu, Z. Sobral Mourão, A. Moore, and E. Sharp, "Low carbon electricity systems for Great Britain in 2050: An energy-land-water perspective," *Appl. Energy*, vol. 228, pp. 928–941, Oct. 2018, doi: 10.1016/j.apenergy.2018.06.127.
[107] "EU reference scenario 2016 : energy, transport and GHG emissions : trends to 2050.," European Commission, Aug. 2016. Accessed: Feb. 13, 2021. [Online]. Available: http://op.europa.eu/en/publication-detail/-/publication/aed45f8e-63e3-47fb-9440-a0a14370f243/language-en/format-PDF
[108] "Heat networks pipeline: January to March 2020," Department for Business, Energy & Industrial Strategy, 2020. Accessed: Feb. 14, 2021. [Online]. Available: https://www.gov.uk/government/publications/hndu-pipeline
[109] "The ten point plan for a green industrial revolution," Department for Business, Energy & Industrial Strategy, 18/11/20202. Accessed: Oct. 22, 2021. [Online]. Available: https://www.gov.uk/government/publications/the-ten-point-plan-for-a-green-industrial-revolution
[110] "Heat networks: building a market framework," *GOV.UK*. https://www.gov.uk/government/consultations/heat-networks-building-a-market-framework (accessed Oct. 25, 2021).
[111] Carbon Trust, "Estimating the cost reduction impact of the Heat Networks Investment Project on future heat networks," Department for Business, Energy &

Industrial Strategy, Nov. 2018. Accessed: Oct. 25, 2021. [Online]. Available: https://www.gov.uk/government/publications/estimating-the-cost-reduction-impact-of-the-heat-networks-investment-project-on-future-heat-networks
[112] National Grid ESO, “Future Energy Scenarios,” 2019.
[113] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 3rd ed. Upper Saddle River, NJ, USA: Prentice Hall Press, 2009.
[114] M. Dash and H. Liu, “Feature selection for classification,” *Intell. Data Anal.*, vol. 1, no. 1, pp. 131–156, Jan. 1997, doi: 10.1016/S1088-467X(97)00008-5.
[115] H. Liu and L. Yu, “Toward integrating feature selection algorithms for classification and clustering,” *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 4, pp. 491–502, 2005, doi: 10.1109/TKDE.2005.66.
[116] I. Guyon and A. Elisseeff, “Special issue on variable and feature selection,” *Introd. Var. Feature Sel.*, vol. 3, pp. 1157–1182, 2003.
[117] M. J.A. Berry and G. Linoff, *Data mining techniques : for marketing, sales, and customer support / M.J.A. Berry, G. Linoff*. 2019.
[118] M. Halkidi, Y. Batistakis, and M. Vazirgiannis, “On Clustering Validation Techniques,” *J. Intell. Inf. Syst.*, vol. 17, no. 2, pp. 107–145, Dec. 2001, doi: 10.1023/A:1012801612483.
[119] Chartered Institution of Building Services Engineers, *Environmental design: CIBSE guide A*. London: CIBSE, 2006.
[120] “LSOA estimates of households not connected to the gas network,” *GOV.UK*. https://www.gov.uk/government/statistics/lsoa-estimates-of-households-not-connected-to-the-gas-network (accessed Aug. 23, 2019).

Appendix A Heat Supply Technologies

A.1 Gas Boilers

The term gas boiler is often used to refer to a natural gas boiler. Although other types of gas boilers exist and are adapted to a different mixture of gases, the technology remains similar. In 2020 in the UK, the most common type of gas boiler installed is the condensing gas boiler. In addition to heating water like a normal gas boiler, the condensing gas boiler uses the latent heat in the flue gases to pre-heat the water to improve the overall efficiency of the system.

Hydrogen boilers are slightly different in their design to accommodate for some of the characteristics of hydrogen as a fuel, such as higher flame speed, greater flammability range and higher burning temperature compared to natural gas. Hydrogen boilers are not currently widely used because hydrogen is still only used in trial areas.

A.2 Biomass and Oil Boilers

Biomass and oil boilers are based on the same technology as gas boilers.

A.3 Resistance Heaters

In a resistance heater, electricity goes through a resistor to release heat. Resistance heaters have an efficiency of 100%. These heaters can take many different forms, including:

- Wall heater;
- Electric baseboard heater;
- Electric radiant heat;
- Electric space heater;
- Electric storage heater.

In the UK, it is common to use electric storage heaters with an Economy Seven tariff for electricity. Cheaper off-peak electricity is used to fill hot water storage, the heat that is stored is then released during peak time, or when needed.

A.4 Heat Pumps

HPs are a mature technology that has the potential to decarbonise a household heating system by using low-carbon electricity to produce heat. The efficiency of a heat pump is described by the COP. This is the ratio of heat produced to electricity consumption. The efficiency of the heat pump depends on the temperature difference between the energy source and the energy sink. For an air-to-air heat pump installed in a dwelling, this is the difference between the outside air temperature and the inside air temperature. Most of the HPs that are installed in the UK are either ASHP or water-to-water GSHP.

A.5 Hybrid Heat Pumps

HHPs are a combination of ASHPs and gas boilers. The heat pump is installed alongside an existing or modified gas boiler. The heat pump is designed to meet most of the heat demand. However, when the heat pump cannot meet peak demand, the system uses the gas boiler. Initially, the system would use natural gas, but conversion to hydrogen would be necessary to meet the net-zero target [112].

A.6 District Heating Networks

District heating is a mature technology that uses heat from single or multiple, large scale sources and distributes it to houses through insulated pipes. This has advantages such as low space requirements for individual dwellings and economies of scale for heat production. Additionally, district heating can be easily changed to a low-carbon heating system at the source, in comparison to changing the individual systems in several houses. District heating could also be used to shift significant levels of heat demand away from peak times, using thermal storage and the thermal inertia of heat networks.

The district heating schemes that are considered in this research were 3rd/4th generation district heating supplying domestic and non-domestic buildings with temperatures of supply/return of ~70/40^{o}C. The location of the energy centres was not discussed in this project.

Appendix B The Steps of a Machine Learning Project

B.1 Introduction

The term “artificial intelligence” was coined during a conference in 1956 by John McCarthy, who defines it as: “the science and engineering of making intelligent machines, especially intelligent computer programs”. This conference also set the path to the creation of the Artificial Intelligence (AI) research field.

Arthur Samuel defined machine learning (ML) as the “field of study that gives computers the ability to learn without being explicitly programmed” (Géron, 2017). A piece of code that is explicitly programmed will have a set of rules that were written manually, whereas a ML-based program will extract the rules from the input dataset.

ML can be considered as a part of AI but it is important to understand that AI is not only ML. Figure B-1 shows that, in addition to ML, AI includes the following fields: natural language processing, knowledge representation, automated reasoning, computer vision and robotics [113].

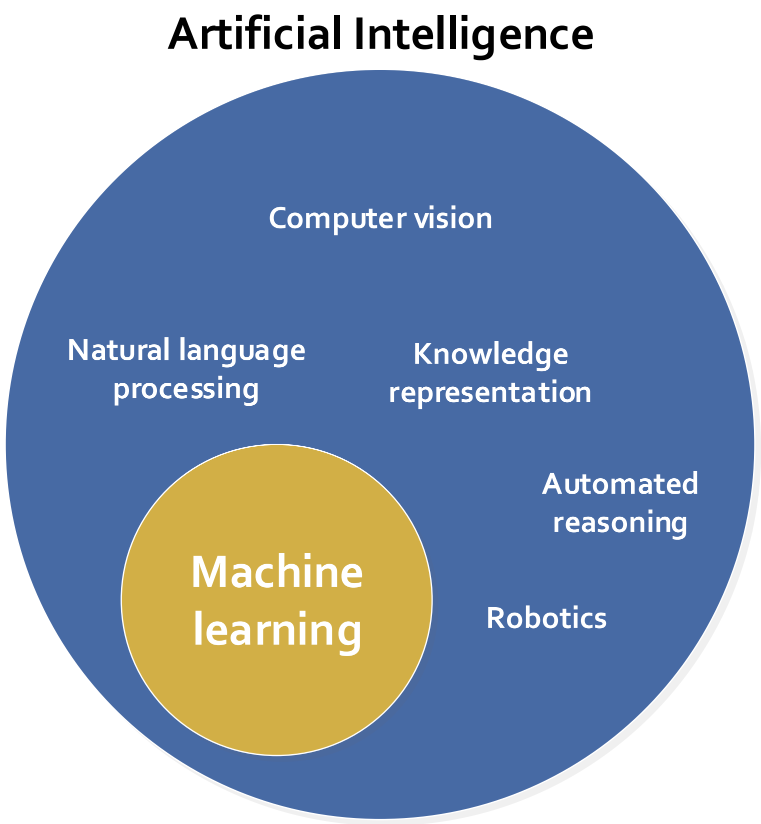


Figure B-1: Illustration of the artificial intelligence field with its subgroups, adapted from [113]

In this thesis, ML will be used in different stages. Hence, some of the specific wording and techniques used in the ML field are described in the following to facilitate the reader's understanding.

B.2 The Steps in a Standard Machine Learning Project

Figure B-2 illustrates the four steps of a standard ML project. The data preparation step consists of collecting data from different sources for it to then be cleaned, pre-processed and sometimes combined. In the feature selection step, the variables carrying the most information regarding the objective of the ML project are identified. These variables are used as inputs to train and test a ML model. Step 3 chooses the ML algorithm and is closely linked to step 4, which validates the result.

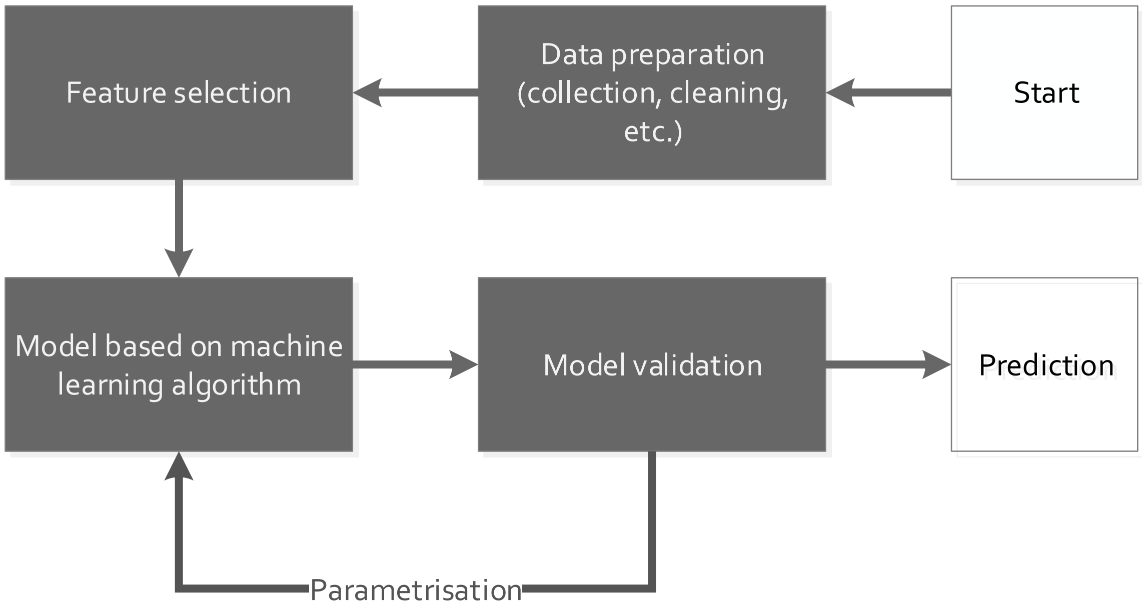


Figure B-2: A standard machine learning pipeline

B.2.1 Data Preparation

The dataset that is collected can be from a variety of sources with a range of inherent quality. Common sources of data are websites, experiments, models and sensors and it is not uncommon to have data with missing records, abnormal values, non-consistent categories, and so on. Hence, the first step is to inspect the data to identify the errors and clean the data, as illustrated by Figure B-3.

Figure B-3: First stage of a ML project

As part of the data cleaning step, different methods can be used, which are dependent on the type of data and type of problem encountered (e.g., missing values in a time series, date formatting, uniformity of data unit and detecting outliers).

B.2.1.1 Missing Values in a Time Series

When there are missing values within a time series, different options are available. A first option is to remove the records with missing values. A second option is to replace the missing values with new values. For example, the new values can be equal to the average of the time series data, zero or if there is a known pattern, the data from another day.

B.2.1.2 Date Formatting

Converting data in the right format is a common task. This is particularly true for dates, which are often encoded as a string chain and need to be converted into a date format to be interpreted correctly by a programming language. The solution usually implies the use of built-in functions that convert string to date when provided with the details of the coding. For instance, when converting the string "17 March 2018" to a date, the function's parameter will indicate that the month is written in letters, the separator is a blank space and that the order is day/month/year.

B.2.1.3 Uniformity of Data Unit

To illustrate this problem, we can take the example of the gas meters in the UK that record the amount of gas flow in cubic meters (SI system) or cubic feet (the imperial system). Hence when working with gas data, it is important to make sure the unit is the same for every record. If it is not the case, then records identified using a different unit need to be converted.

B.2.1.4 Detecting Outliers

Outliers can be difficult to deal with and will require knowledge of the data at hand to choose the right action. If we know that the data follows a normal distribution, then it could be relevant to create a filter that would remove data that fall outside a three standard deviations window.

After the dataset is cleaned, it can be analysed to uncover further information. The next step is to identify variables that carry the most information relative to the objective.

B.2.2 Feature Extraction/Selection

In the ML field, the term *feature* is used as a synonym to an *independent variable*. The independent variables are the input variables and the dependent variables are the outputs of the model. A set of carefully selected features will allow the prediction of the output of a model. Consequently, finding the most relevant features relative to an output is a crucial task in a ML project. This step is referred to as feature extraction or feature selection.

Feature selection is the process of choosing the right features that would yield the best result when input to a ML algorithm. This step directly influences the output of the model, thus it is often considered the most important task in a ML project. There are several reasons that explain its importance, the first and most obvious is that by removing irrelevant features and redundant features [114], [115] the computation time will be reduced as the model has fewer data to process and deal with. Second, this will also help with the quality of the results as the final model will only use features carrying information relevant to the prediction of the output. Furthermore, it helps with readability and interpretability which is often disregarded but important when trying to understand the results. It is easier to interpret the output of a problem when there are only a few variables involved.

There are three main approaches to feature selection, which are the filter, wrapper and embedded [116] approaches, which will be described in the following subsections.

B.2.2.1 The Filter Approach

The filter approach pre-selects features based on statistical tests for their correlation with the targeted variable. Hence, the selection of the features is performed independently of the algorithm as seen in Figure B-4.

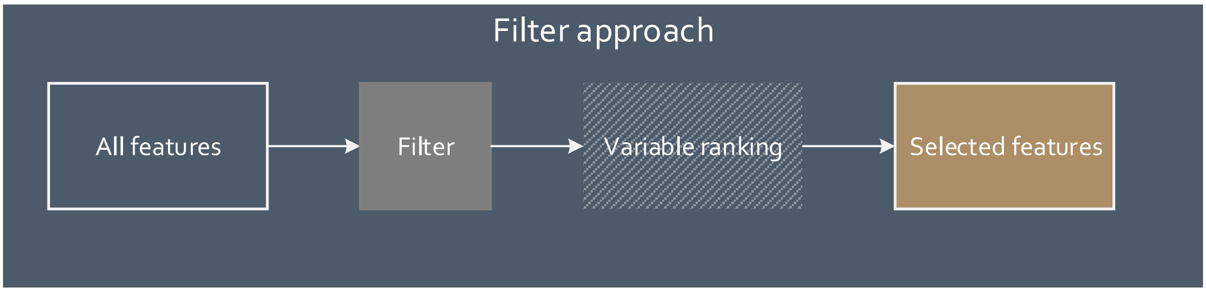


Figure B-4: Diagram of the filter approach

In the filter approach, the objective is to rank the variables based on a criterion that assesses their correlation with a target variable. Depending on the characteristics of the variables, different methods can be used, some of the most common filters are Person's correlation, Anova and Chi-square.

B.2.2.2 The Embedded Approach

The embedded method is a 'black box' approach. It leverages features of some generic ML algorithms to identify the most relevant features (see Figure B-5), such as regularization methods for regression algorithms and purity methods for decision tree-based algorithms.

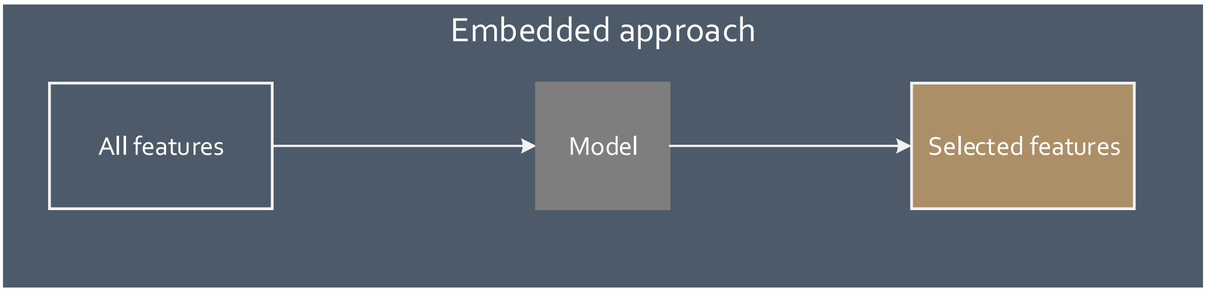


Figure B-5: Diagram of the embedded approach

B.2.2.3 The Wrapper Approach

Figure B-6 shows a diagram of the wrapper approach, which is based on an iterative process in which the ML algorithm, which is used in the final model of the project, is used in a loop to assess the performance of different sub-datasets. The sub-dataset yielding the best performance is identified and its list of features extracted. This is often the approach that generates the best results because it uses the final ML algorithm as part of the evaluation method, but it is also computationally expensive.

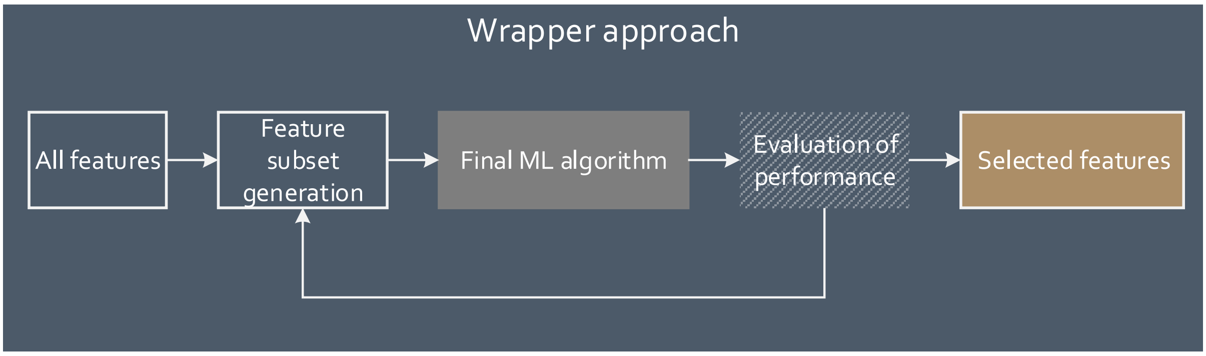


Figure B-6: Diagram of the wrapper approach

B.2.3 Machine Learning Algorithms

There are three main types of algorithms in ML: supervised learning algorithms, unsupervised learning algorithms and reinforced learning algorithms. Depending on the objective of a project, the choice of the algorithm for the model developed will be different as each ML algorithm has a different purpose.

B.2.3.1 Supervised Learning

Supervised learning algorithms are used to map the specific relationships or structure found in the input variables X that can correctly predict an output variable y. The objective is to approximate the function so that for any new input variables X' you can predict the output variables y'. Two main types of problems are solved by this type of algorithm: classification and regression problems. The classification problem is the case where the inputs variables are mapped to an output represented by a categorical variable. The regression problem is the case where the input variables are mapped to a continuous output variable. In both cases, the quality of the prediction is determined by the quality of the training dataset.

Example of a classification algorithm: the decision tree

Decision tree algorithms are popular in the world of ML due to their high interpretability and their proximity to how humans classify. The learning process is based on splitting a training dataset into subsets until the target variables of a subset all have the same values or the splitting process no longer adds value to the prediction. Building upon the boxed text example above and assuming a training dataset including the number of edges of the shapes, a decision tree is built (see Figure B-7). In this tree, the ellipses represent the characteristic of a feature, the branches are the decisions and the blue boxes are the leaves/outcomes.

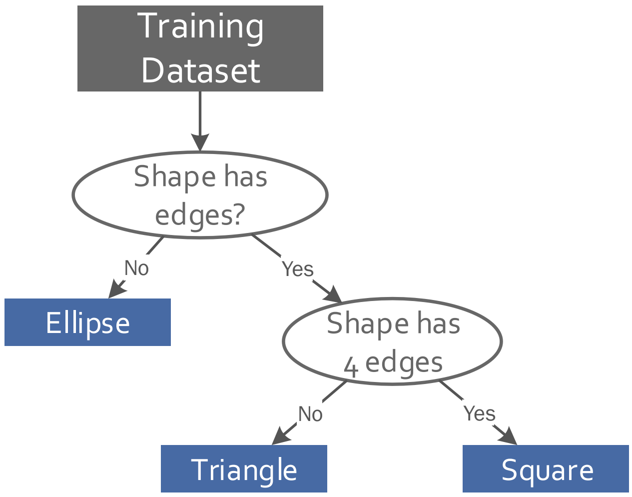


Figure B-7: Example of a decision tree showing the learning process to classify shapes

On a computer, a decision tree for classification is usually built by using a criterion, such as Gini impurity or information gain.

Example of a regression algorithm: the linear regression

A linear regression algorithm is used to predict a continuous target y based on an independent variable x. It can be defined as:

$$y = ax + b$$

With a and b, the two parameters calculated by minimising the error between the Ys and Xs in the training dataset. A common criterion for the error is the sum of the squared residuals.

In the ML field, linear regression models are mostly used for forecasting purposes.

Extreme gradient boosting using XGboost

In this research, an extreme gradient boosting algorithm was used to develop models to predict the heat and energy consumptions of heating technologies. A gradient boosting algorithm is based on an ensemble method where the results of several models are combined into one by minimising a loss function using a gradient descent algorithm. XGboost is an implementation of this algorithm, which combines predictions from several decision trees with a gradient boosting algorithm [61], and can be used to predict continuous or categorical data.

B.2.3.2 Unsupervised Learning

Unsupervised learning algorithms differ from supervised learning algorithms by the fact that they do not aim to predict anything. They have a more exploratory role in the way that they look to identify patterns in the training dataset, and thus they are not given any specific target. Unsupervised learning algorithms are used for two main purposes: clustering and association. The concept of clustering is presented in the following boxed text. Association aims to discover rules between variables that describes a large portion of the dataset, for instance when A happens B often happens.

Example of a clustering algorithm: the K-means algorithm

The K-means algorithm is one of several algorithms available for clustering. It is initialized by specifying the number of clusters N and the position of their centroids. The algorithm starts by dividing the input dataset into N clusters and it then calculates their inertia, which is the within-cluster-sum-of-squares. It iterates through the different position of the centroids until the inertia is minimised.

Here is an example of a clustering algorithm. A training dataset is constituted of different coloured shapes. The objective of the algorithm is to cluster these shapes into different groups. One possible output of the model could be three clusters, with: cluster 1 representing the triangle shapes, cluster 2 the squares and cluster 3 the ellipses as shown in Figure B-8. Another possible output of the model could be four clusters with each cluster representing a specific colour: green, blue, yellow or red.

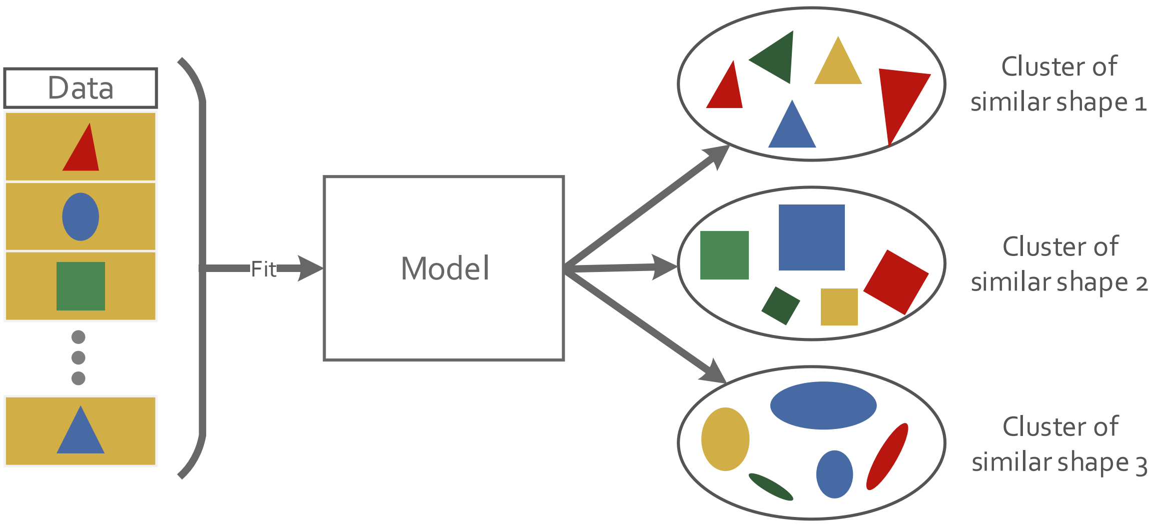


Figure B-8: A potential output of a clustering algorithm having a dataset of coloured shapes as input

Example of an association algorithm: the Apriori algorithm

The Apriori algorithm is used to find frequent itemset and relevant association rules from the study of a large dataset. The first step of the algorithm is to calculate the frequency of each itemset and then filter the result based on a defined threshold. The second step is to calculate the frequency of a pair of itemsets and then filter those with high frequency. The same process is reiterated with a different size of item sets until there is no more association found.

B.2.3.3 Reinforcement Learning

Reinforcement learning differs from supervised learning because there is no label in the training dataset to learn from and from unsupervised learning because there is an objective to the algorithm in the form of reward. The simplified diagram presented in Figure B-9 represents the functioning of a reinforcement learning algorithm. An agent sends information to act upon a given environment. The state of the environment resulting from this action and the reward quantified positively or negatively are then processed by the agent. This loop is repeated with different inputs, which allows the agent to determine the cost-optimal behaviour to adopt or path to take in a specific situation. This type of learning algorithm was popularised in learning to play games such as Go[12] and Chess.

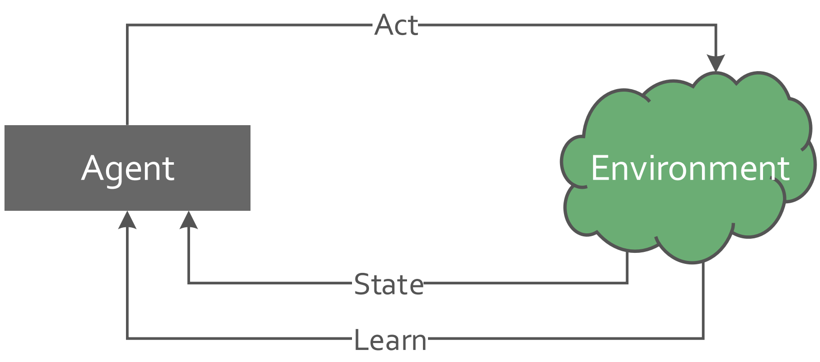


Figure B-9 : Simplified diagram of the reinforcement learning process

B.2.4 Model Validation

After deciding on the features to include in the training dataset and the type of algorithm, the next step is to train the model. The training part is crucial because it can lead to several problems that can alter the outputs of the model. There are a number of

[12] AlphaGo is a computer program that plays the board game Go, https://deepmind.com/research/alphago/

techniques to consider depending on the type of algorithm chosen to help to tune the parameters and estimate the accuracy of a model.

For supervised learning, the most common technique is called cross-validation. This consists of splitting the training dataset into k folds, training the algorithm with the model with $k - 1$ folds and testing the accuracy of the model by comparing its prediction with the value from the remaining fold. The process is repeated k times, until all combinations are completed. The results are then aggregated and analysed. When good results are achieved following this methodology, it gives confidence that the model will behave similarly when dealing with new input data.

For clustering, the validation method is more dependent on the algorithm chosen and the type of data. There are two criteria proposed for validation: compactness (i.e., the members within a cluster should be as close as possible from each other) and separation (i.e., the distance between clusters should be as large as possible) [117]. A number of indices aim to evaluate these criteria [118].

In the case of association algorithm and reinforcement learning, the validation method is embedded within the algorithm making external validation recurrent.

Appendix C Additional Tools Using the Annual Heat Demand

C.1 Temperature Correction of the Annual Heat Demand

The energy consumption figures displayed on an EPC are calculated using a typical temperature profile, which is location-specific and is extracted from the SAP guidelines. Hence, heat demand estimated using EPCs can be considered to be temperature corrected.

Table C-1 shows the monthly average temperature for Wales from the SAP 2012 guidelines. Using this profile, the number of degree-days for the year was calculated using a 15.5°C base temperature (this is a temperature threshold above which there is a need for heating buildings). For Wales, there were 2,059 degree-days.

Table C-1: Monthly temperature (°C) from SAP 2012 guidelines

Month (January:1, December:12)	1	2	2	4	5	6	7	8	9	10	11	12
Average temperature Wales	5	5.3	6.5	8.5	11.2	13.7	15.3	15.3	13.5	10.7	7.8	5.2

Using this value, the normalised annual heat demand by degree day (NHD) for each dwelling category can be calculated. Equation 24 shows the formula used for Wales for a dwelling category i:

$$NHD_i = \frac{Heat\ demand_i}{2{,}059} \tag{24}$$

To estimate the heat demand of a dwelling archetype for a target year, and thus a specific temperature profile, the NHD for each dwelling category was multiplied by the number of degree-days in the target year.

Equation 25 shows the formula used to calculate the heat demand for a dwelling category i in 2018 in Wales, 1,687 degree-days were recorded for this year:

$$Heat\ demand\ 2018_i = NHD_i \times 1{,}687 \tag{25}$$

Example: Temperature correction of the Cardiff heat demand in 2018

Figure C-1 shows the average annual heat demand for the detached gas boiler archetype in Cardiff from the EPC-based method (weather corrected) and based on the temperature profile of 2018. Because 2018 was a warmer year on average than the temperature profile used to produce EPCs, a decrease in the annual heat demand is observed.

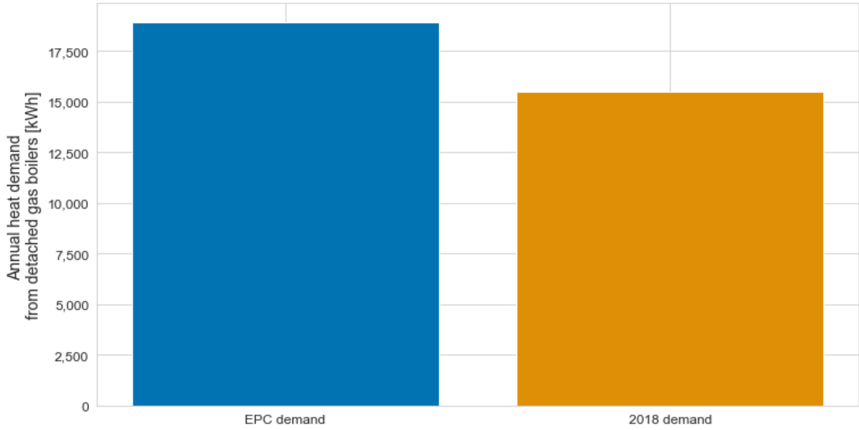


Figure C-1: Bar charts showing the estimated heat demand for a detached gas boiler archetype using the EPC and the corrected demand for 2018 based on the degree-days method.

C.2 Sizing of Heat Pump Systems

In this section, a method for sizing a heat pump[13] and its backup heating system is discussed. This is used to accurately estimate the electricity consumption of the heat pump and its backup heating system during cold temperatures. Recommendations from CIBSE Guide A – Environmental design [119] and Microgeneration Installation Standard (MIS3005) [66] were used to estimate the average size of heat pump for different dwelling types.

The average heat loss for various dwelling types was calculated using their average annual space heating demand calculated from EPC of buildings, and Heating Degree Day (HDD):

$$\text{Heat loss}\left(\frac{\text{kW}}{\text{°C}}\right) = \frac{\text{Annual space heating demand (kWh)}}{\text{HDD (°C day)x } 24\,\frac{\text{hour}}{\text{day}}} \tag{26}$$

The thermal output of the heating system should compensate for the heat loss at chosen ‘internal design temperature’ and ‘outside design temperature’. A simplified internal design temperature of 21°C [66] and outside design temperature of -3.2°C were chosen

[13] Sizing of other heating technologies will be done in Task 7 of WP2. This will be done to estimate the capital cost of heating systems. The reason why sizing of heat pumps is done in this report is to have a better idea of the temperature below which the back-up heating system starts operating because this affects the electricity consumption of the heating system.

for buildings in South Wales. According to MIS3005 [66], any supplementary in-built electric heater shall be designed to not operate above the internal temperatures or the external temperatures. Therefore, we determined the size of the heat pump to be able to compensate for the heat loss at 24.2℃ temperature difference. Table C-2 shows the average heat loss of different dwelling types at the design temperatures (24.2℃ temperature difference). The size of HPs available in the market may not be exactly equal to the values of heat loss shown in Table C-2, therefore a heat pump will be chosen whose size is closest to (and greater than) the heat loss values at design temperature.

Table C-2: Average heat loss of dwelling types at the internal design temperature of 21℃ and outside design temperature of -3.2℃ in Cardiff, Swansea and Newport

	Detached	Semi-detached	Terraced	Flat
Thermal output (kW)	10.9	6.9	5.5	3.2

Backup heating is required when the main heating system is insufficient to cover the heat demand (space heating and hot water) when the OAT is below the design temperature. According to MIS3005 [66], it is not compulsory to install a backup heater, thus its installation will depend on the customer decision. For instance, in the RHPP trial data [62], more than half of the heat pump installations for which relevant information was available (i.e., if they are equipped with a backup heating system) did not have a backup heating system.

In this research, when the OAT falls below the design temperature, additional heat is needed from a backup heating system. According to CIBSE environmental design guide A p48 [119], the lowest daily OAT observed in Cardiff was around -7℃ between 1882 and 2002. The average heat losses for different dwelling type that needs to be compensated through a backup heating system are shown in Table C-3. Similar to the heat pump, the actual size of a backup heating system depends on the size of available products in the market.

Table C-3: Average heat loss of dwelling types that need to be supplied by backup heating. The heat loss value calculated for a temperature difference of 3.8 ℃ (minimum daily outside temperature of -7℃ - outside design temperature of -3.2℃).

	Detached	Semi-detached	Terraced	Flat
Thermal output (kW)	1.7	1.1	0.9	0.5

Appendix D Training Data and Performance of the Models When Used to Synthesise Heat Production and Energy Consumption of ASHPs, GSHPs, Resistance Heaters and Gas Boilers

D.1 The Trial Dataset

Figure D-1 shows a snapshot of the heat pump trial dataset at half-hourly resolution with data for individual HPs.

	Date	Electricity consumption (kWh)	Heat production (kWh)	HP ID	Heat pump type
0	2013-08-01 05:30:00	2.146000	4.540000	RHPP5104	GSHP
1	2013-08-01 06:00:00	0.226154	0.445385	RHPP5104	GSHP
2	2013-08-01 06:30:00	0.000000	0.000000	RHPP5104	GSHP
3	2013-08-01 07:00:00	0.000000	0.000000	RHPP5104	GSHP
4	2013-08-01 07:30:00	0.000000	0.000000	RHPP5104	GSHP
...	...	...	...	...	...
6242049	2014-12-31 20:00:00	2.055000	7.005000	RHPP5818	GSHP
6242050	2014-12-31 20:30:00	2.595000	5.535000	RHPP5818	GSHP
6242051	2014-12-31 21:30:00	1.882500	7.012500	RHPP5818	GSHP
6242052	2014-12-31 22:30:00	1.494000	4.710000	RHPP5818	GSHP
6242053	2014-12-31 23:30:00	2.177143	6.008571	RHPP5818	GSHP

Figure D-1: Snapshot of the trial dataset including electricity consumption and heat production data for each GSHP and ASHP

Figure D-2 shows the ASHPs trial dataset at half-hourly resolution including average heat production, electricity demand of a pool of ASHPs, and the daily average OAT.

	Electricity consumption (kWh)	Heat production (kWh)	Daily average temperature
index			
2013-10-01 00:00:00	0.198429	0.503114	14.3
2013-10-01 00:30:00	0.204122	0.395570	14.3
2013-10-01 01:00:00	0.257641	0.722667	14.3
2013-10-01 01:30:00	0.215068	0.416838	14.3
2013-10-01 02:00:00	0.197304	0.840348	14.3
...	...	...	...
2015-02-28 21:30:00	0.718300	2.095522	7.8
2015-02-28 22:00:00	0.706236	1.953201	7.8
2015-02-28 22:30:00	0.562588	1.453866	7.8
2015-02-28 23:00:00	0.434302	0.924159	7.8
2015-02-28 23:30:00	0.327345	0.863470	7.8

Figure D-2: Aggregated trial dataset of ASHPs with outside air temperature

D.2 The Capacity of Heat Pumps by Type and Dwelling Type

The installed capacity of ASHPs and GSHPs by dwelling type and the number of bedrooms is presented in Figure D-3 and Figure D-4. Only 74 dwellings with ASHP and 49 dwellings with GSHP had information about property type, thus it might not be representative of the full dataset.

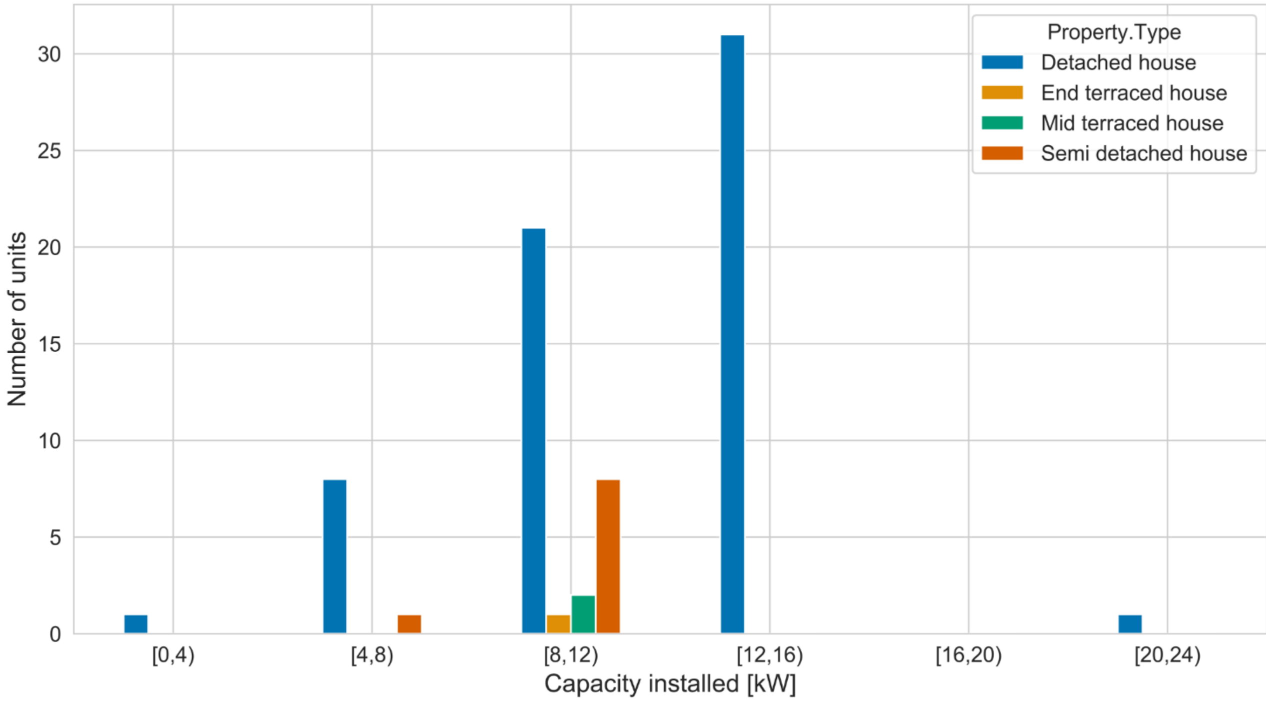


Figure D-3: Number of ASHP by capacity installed and property type in the dataset

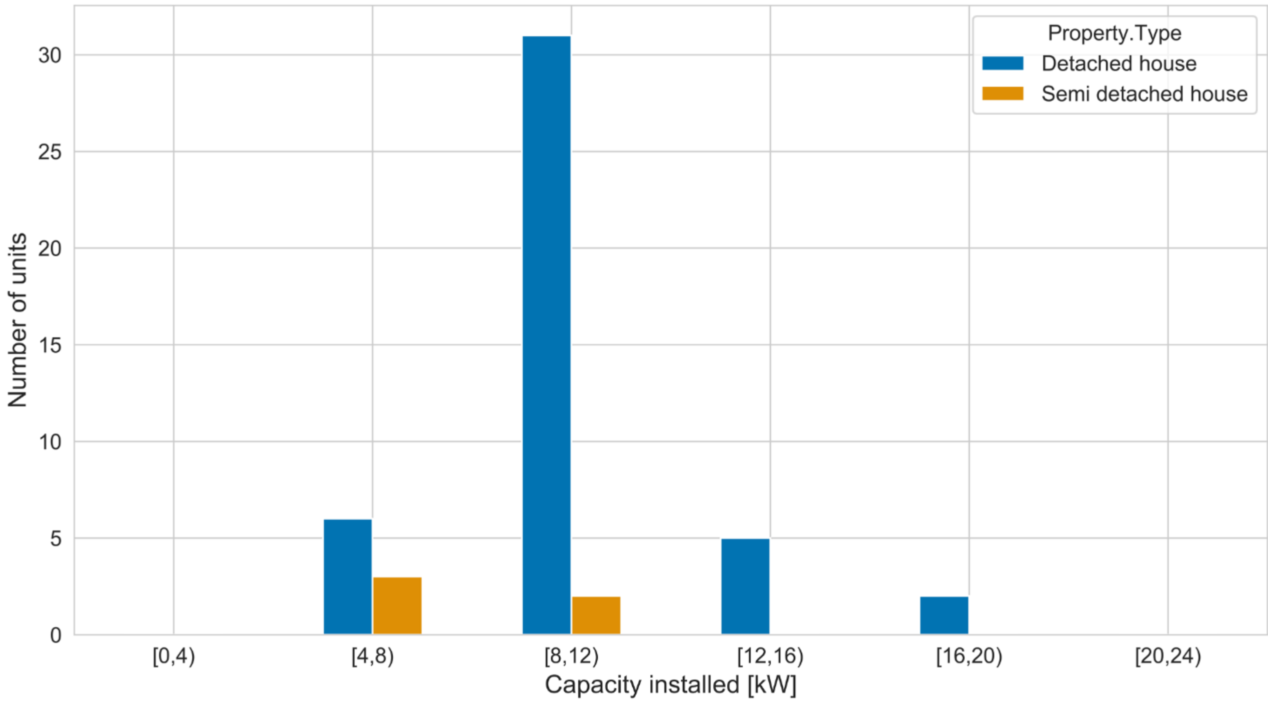


Figure D-4: Number of GSHP by capacity installed and property type in the dataset

D.3 Distribution of the COP of Individual HPs

D.4 Performance of the Combined Models

D.4.1 ASHPs

Table D-1 shows the performance of the first models at synthesising the heat production profile of ASHPs calculated from a five-fold cross-validation (CV) procedure. The best model combines the main model with models predicting values above the 90% percentile. This combination improves the accuracy of the main model in predicting peaks by 2%. No significant changes were noticed in the total heat supplied.

Table D-1: Average performances of different models synthesising heat production profile of ASHPs from a five-fold CV procedure.

Metrics	Main model	Main model + models for: 95%, 99% percentiles	Main model + models for: 90%, 95% percentiles	Main model + models for: 90% percentiles	Main model + models for: 95% percentiles	Main model + models for: 99% percentiles
Coincidental peak error for values above 99% percentile compared to actual data	-11%	-10%	-9%	-9%	-10%	-11%
Error in the area under the curve compared to actual data	1%	1%	1%	1%	1%	1%

Table D-2 shows the performance of the different type of models when used to synthesise the electricity demand profile of ASHPs calculated from a five-fold CV procedure. All of the models used the synthesised heat production profile from the best model of Table D-1 as one of their input features. The best model combines the main model with models predicting values above the 90% and 95% percentile. This combination improves the accuracy of the main model in predicting peaks by 4%.

Table D-2: Average performances of different models synthesising electricity demand profile of ASHPs from a five-fold CV procedure.

Metrics	Main model	Main model + models for: 95%, 99% percentiles	Main model + models for: 90%, 95% percentiles	Main model + models for: 90% percentiles	Main model + models for: 5%, 95% percentiles	Main model + models for: 1%, 99% percentiles
Coincidental peak error for values above 99% percentile compared to actual data	-9%	-6%	-5%	-6%	-6%	-8%
Error in the area under the curve compared to actual data	1%	1%	1%	1%	1%	1%

D.4.2 GSHPs

Table D-3: Average performances of different models synthesising heat production profile of GSHPs from a five-fold CV procedure.

Metrics	Main model	Main model + models for: 95%, 99% percentiles	Main model + models for: 90%, 95% percentiles	Main model + models for: 90% percentiles	Main model + models for: 95% percentiles	Main model + models for: 99% percentiles
Coincidental peak error for values above 99% percentile compared to actual data	-10%	-8%	-7%	-6%	-8%	-9%
Error in the area under the curve compared to actual data	-1%	-1%	-1%	-1%	-1%	-1%

Table D- 4: Average performances of different models synthesising electricity demand profile of GSHPs from a five-fold CV procedure.

Metrics	Main model	Main model + models for: 95%, 99% percentiles	Main model + models for: 90%, 95% percentiles	Main model + models for: 90% percentiles	Main model + models for: 95% percentiles	Main model + models for: 99% percentiles
Coincidental peak error for values above 99% percentile compared to actual data	-8%	-6%	-5%	-5%	-6%	-7%
Error in the area under the curve compared to actual data	0%	0%	0%	0%	0%	0%

D.4.3 Natural Gas/Hydrogen Boilers

Table D-5: Average performances of different models synthesising heat production and gas demand profile of gas boilers from a five-fold CV procedure.

Metrics	Main model	Main model + models for: 95%, 99% percentiles	Main model + models for: 90%, 95% percentiles	Main model + models for: 90% percentiles	Main model + models for: 95% percentiles	Main model + models for: 99% percentiles
Coincidental peak error for values above 99% percentile compared to actual data	-6%	-1%	0%	-2%	-1%	-5%
Error in the area under the curve compared to actual data	0%	1%	1%	1%	1%	0%

D.4.4 Resistance Heaters

Table D- 6: Average performances of different models synthesising heat production and electricity demand profile of resistance heaters from a five-fold CV procedure.

Metrics	Main model	Main model + models for: 95%, 99% percentiles	Main model + models for: 90%, 95% percentiles	Main model + models for: 90% percentiles	Main model + models for: 95% percentiles	Main model + models for: 99% percentiles
Coincidental peak error for values above 99% percentile compared to actual data	-17%	-13%	-11%	-11%	-13%	-16%
Error in the area under the curve compared to actual data	-1%	0%	0%	0%	0%	-1%

D.5 Density Distributions of Original and Synthesised Profiles

The density distribution profiles for the same period were built using the original data and the data synthesised using the models for each technology.

D.5.1 ASHPs

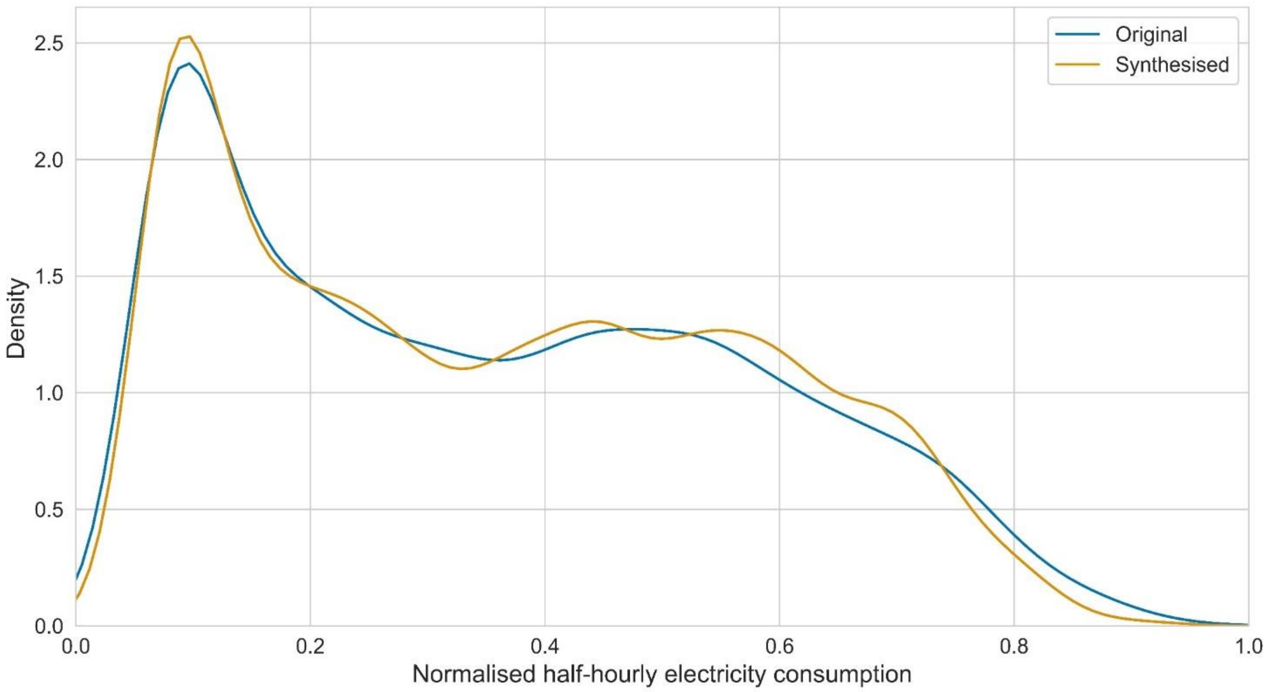


Figure D-5: Density distribution between the trial data and the synthesised profile using the model for ASHP

D.5.2 GSHPs

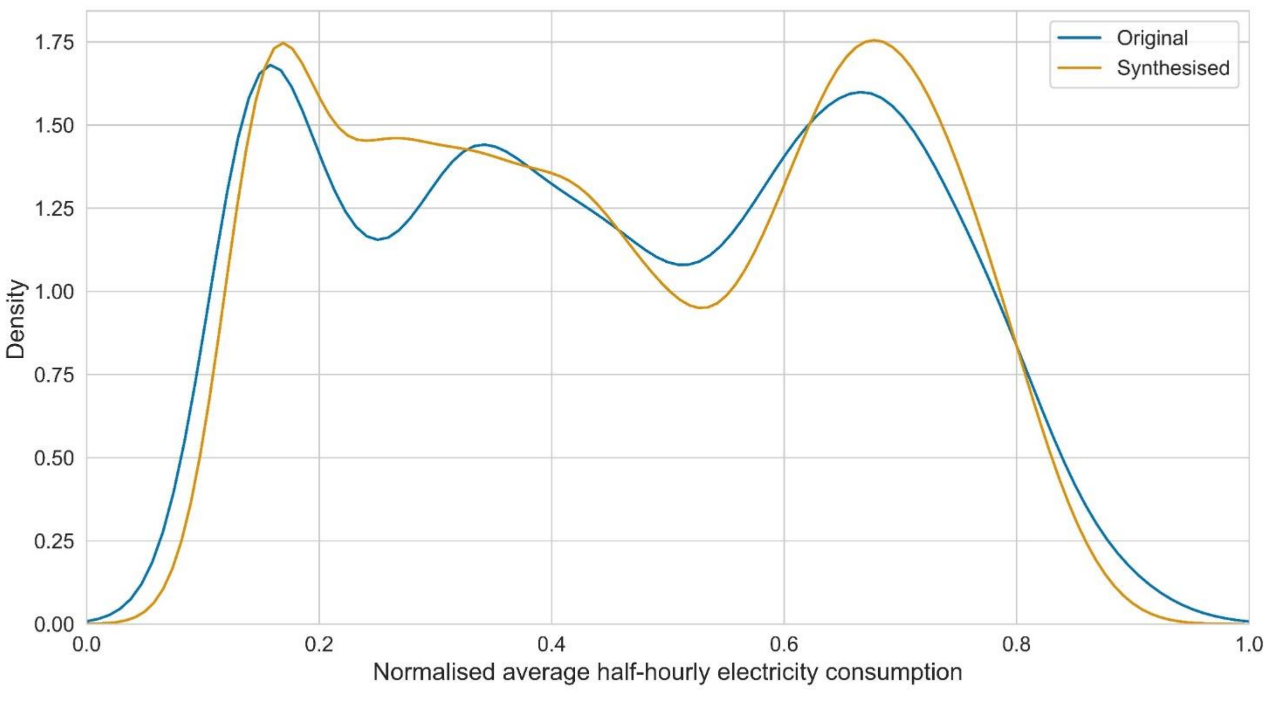


Figure D-6: Density distribution between the trial data and the synthesised profile using the model for GSHP

D.5.3 Natural Gas/Hydrogen Boilers

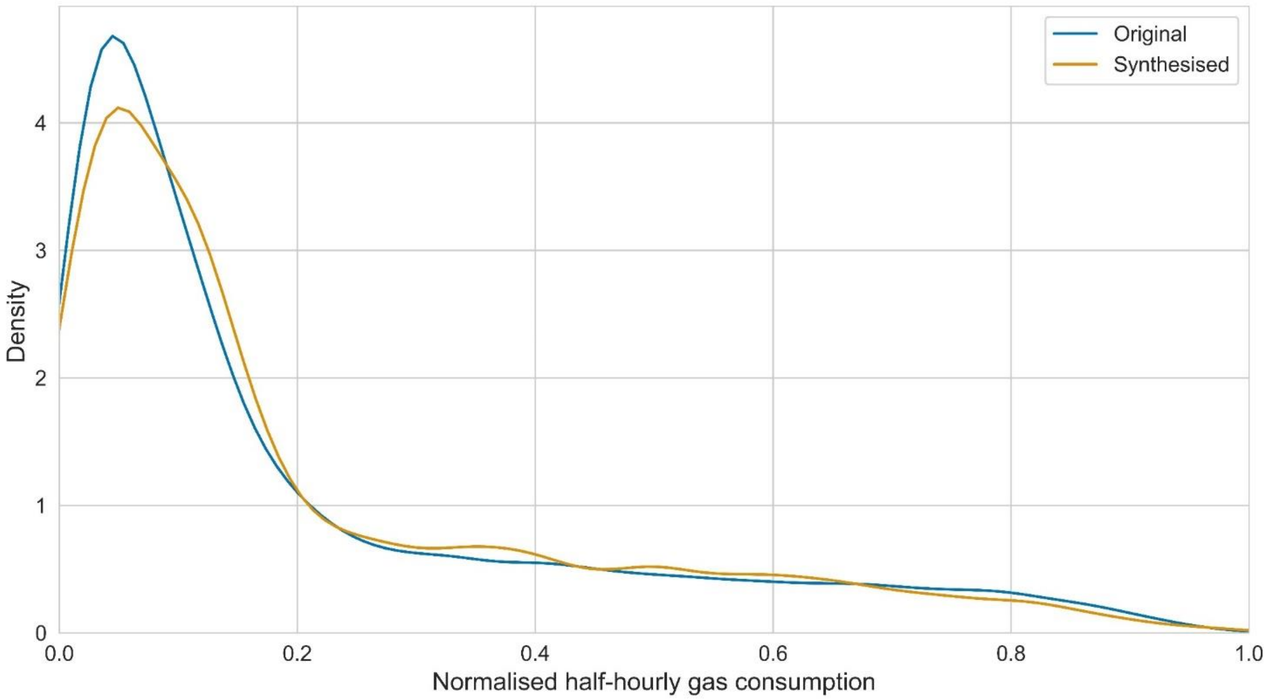


Figure D-7: : Density distribution between the trial data and the synthesised profile using the model for boilers

D.5.4 Resistance Heaters

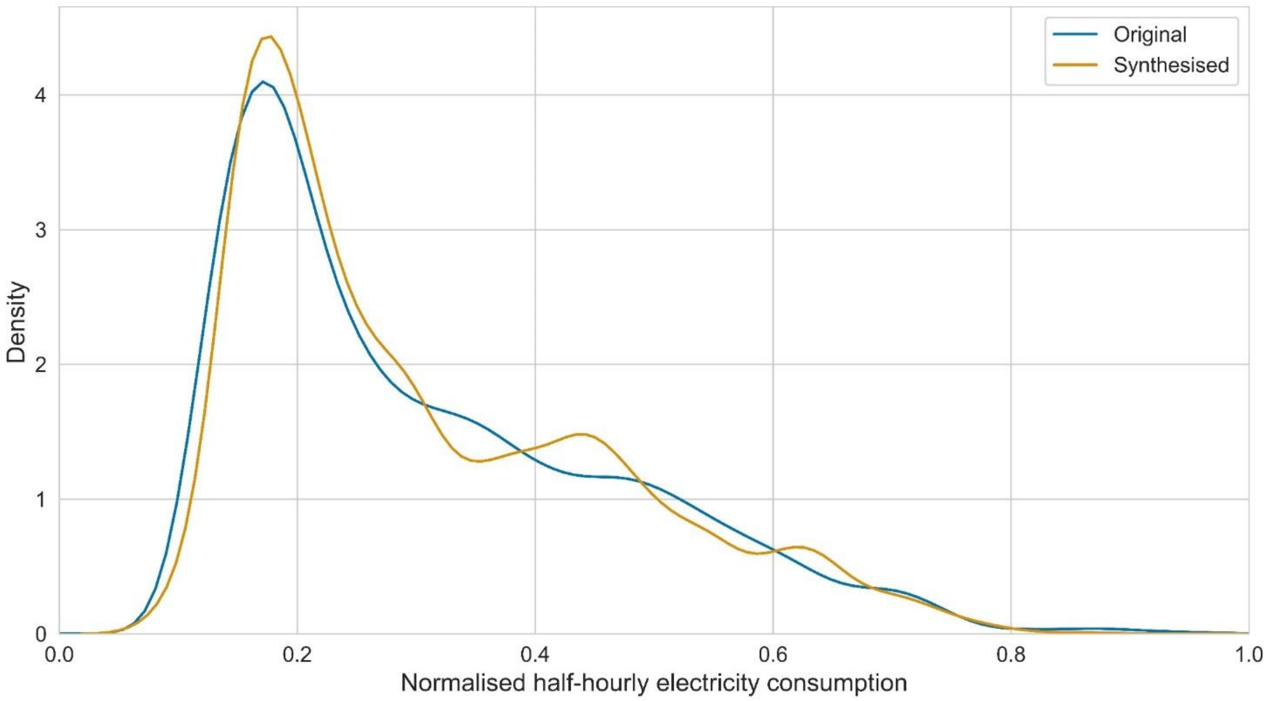


Figure D-8: Density distribution between the trial data and the synthesised profile using the model for resistance heaters

Appendix E Assumptions and Results for the Two Decarbonisation Pathways

E.1 District Heating in the Electrification Pathway

E.1.1 Assumptions

A range of technologies can supply heat to a district heating network. For this project, only the *electrification* pathway included district heating schemes as part of the heat supply mix. The heat supply units were electric boilers, geothermal HPs[14] and energy from waste (EfW) plants.

The electric boilers and the geothermal HPs used electricity as their energy source. The electric boilers were peak load plants and the geothermal HPs intermediate or baseload plants. The COP of geothermal HPs used was 4.94 [71]. The EfW units were used as baseload plants.

The EfW units were only considered for the city of Cardiff as one 30 $MW_{electricity}$ plant[15] is already operational and a second 15 $MW_{electricity}$ plant is planned to be built[16]. These units use municipal waste from South Wales, including Newport and Swansea, making it unlikely for additional EfW units to be built in these two cities. The CAPEX and OPEX of the EfW units for the district heating were considered to be zero.

The maximum capacity installed for this technology in 2030, 2040 and 2050 was 45 $MW_{electricity}$. Based on a 23.7% electricity efficiency and 79.6% heat efficiency[17] (figures are for large EfW CHP units with 80/40°C supply/return temperature from [71]), the maximum thermal power was 153 MW_{heat}.

[14] A geothermal heat pump is a geothermal heat-only plant with electric heat pump. The source of heat is a bore hole with a depth of 1200m. The supply/return temperature is expected to be around 80/40°C.

[15] https://www.designfireconsultants.co.uk/codeless_portfolio/cardiff-efw/

[16] https://www.cewales.org.uk/latest-news/15mw-energy-waste-plant-planned/

[17] The total efficiency exceeds 100% as it is calculated using the LHV of the inputs fuel.

E.1.2 Results

To assess the impact of the size of thermal storage on the cost of district heating, the following steps were used:

1. Creation of a district heating profile using no thermal storage,
2. Creation of additional district heating profiles based on a different level of peak demand reduction based on profile from step 1,
3. Calculation of the size of the thermal storage and the capacity installed of the heat supply units for each profile,
4. Calculation of the total cost (CAPEX+OPEX) of the system,
5. Comparison of the results.

Considering a district heating with an annual domestic heat demand of 500 GWh per year, half-hourly profiles were created for three levels of peak demand reduction: 0%, 4% and 7%.

Figure E-1 shows some characteristics of these profiles. The figure on the left-hand side shows half-hourly heat demand for a week in January. The figure on the right-hand side shows a part of the load duration curves built using these profiles. With the increase in the amount of peak shaving, there is a shift in the heat demand from peak times to off-peak times.

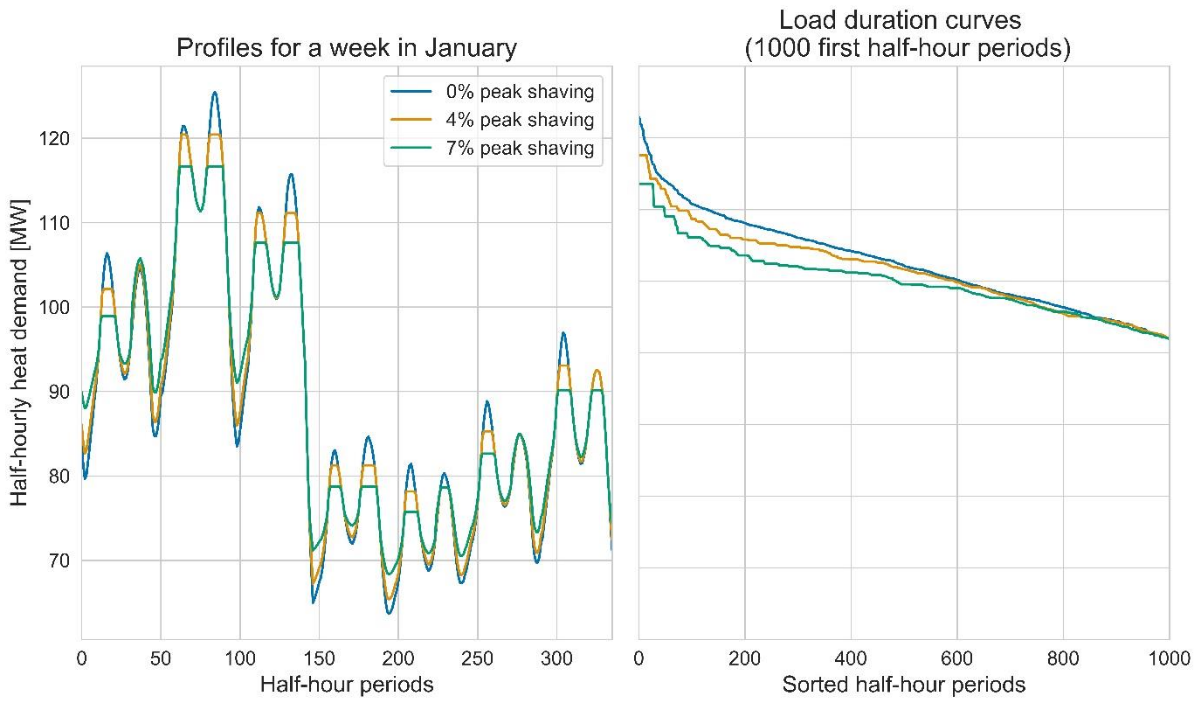


Figure E-1: District heating profiles with different level of peak demand reduction: 0%, 4% and 7%. The figure on the left-hand side shows the half-hourly heat demand for the three profiles for a week in

January. The figure on the right-hand side shows how the load duration curves are impacted by the amount of peak shaving.

Figure E-2 shows the size of the thermal storage required to reach these levels of peak shaving and a comparison of the total costs of each system relative to a system without thermal storage. There is no linear relationship between the size of the thermal storage and the increase in peak demand reduction, while a doubling of the amount of peak shaving is not equivalent to a double in size of the thermal storage. Based on the control for the thermal storage defined in this project, it appears that maximising the size of the thermal storage leads to a lower cost for the system. However, the decrease in system cost was not significant and multi-day thermal storage may be required to increase the savings.

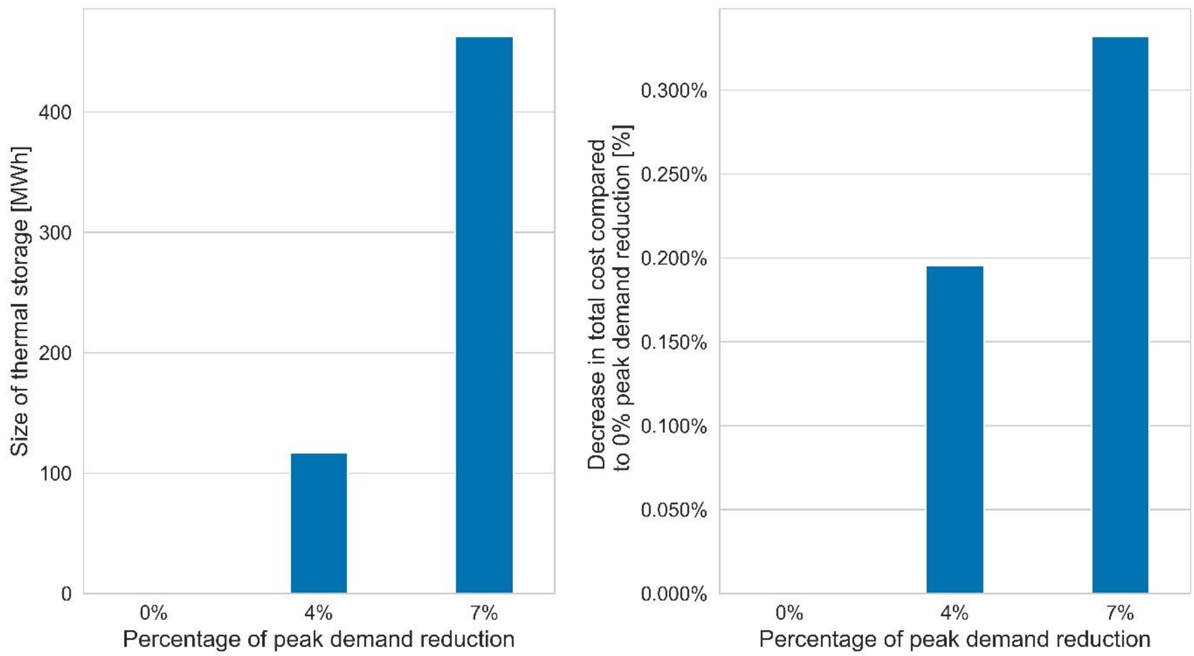


Figure E-2: Size of the thermal storage and their impact on the cost of the district heating system.

Heat supply units and thermal storage in Cardiff, Swansea and Newport.

Using the method developed in Section 4.3 , the thermal storage capacity was assessed for all of the district heating schemes identified in Cardiff, Swansea and Newport. Figure E-3 shows the total thermal storage capacity that was obtained.

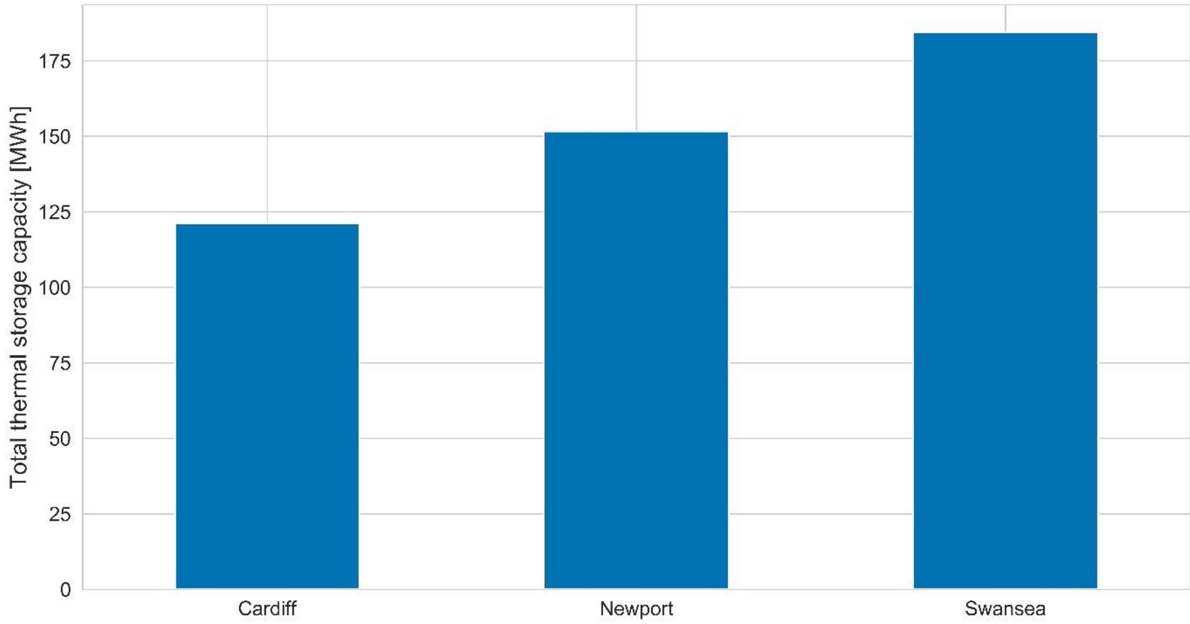


Figure E-3: Thermal storage capacity installed for the three local authorities in 2030 in the electrification pathway.

Figure E-4 shows the total installed thermal capacity of the units supplying heat to the district heating in the three local authorities in 2030.

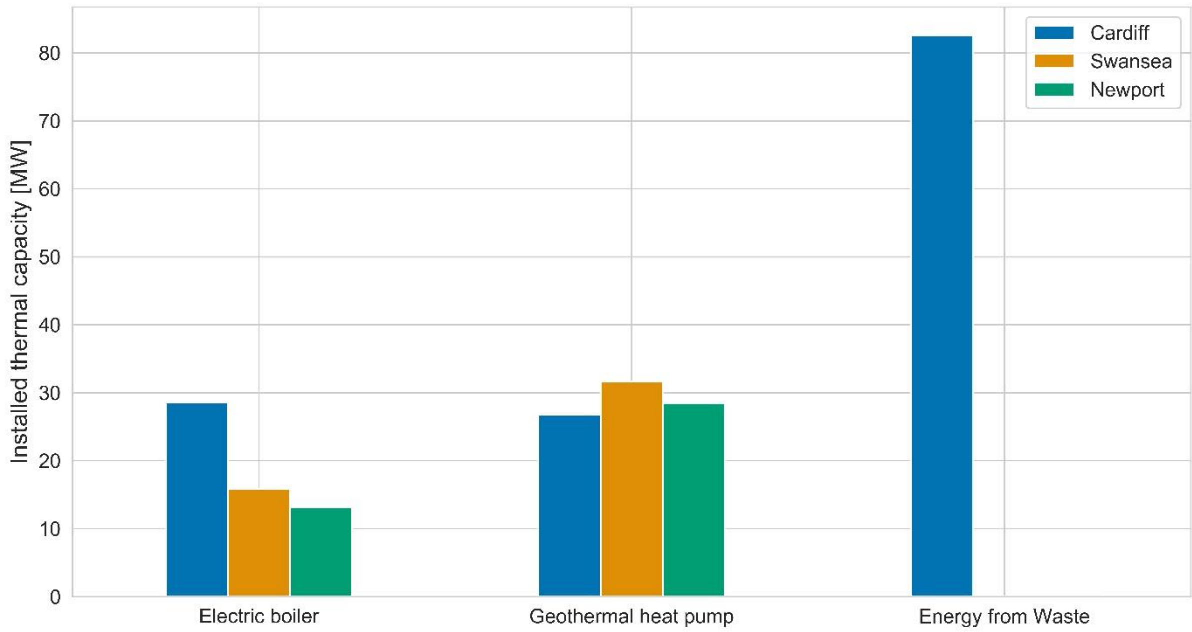


Figure E-4: Total installed thermal capacity of units supplying heat to district heating in Cardiff, Swansea and Newport in 2030.

E.2 Heat Production and Energy Demand Profiles for 2030 and 2040 for the Two Decarbonisation Pathways

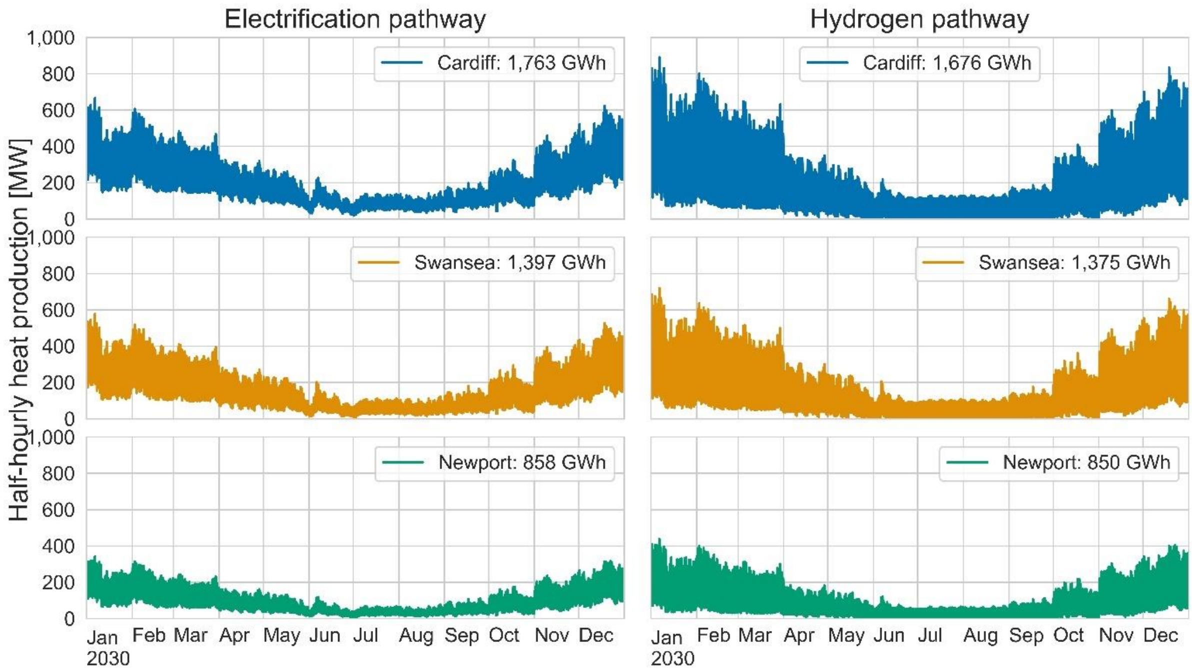


Figure E-5: Aggregated half-hourly heat production profiles of Cardiff, Swansea and Newport in 2030 for the electrification and hydrogen pathways.

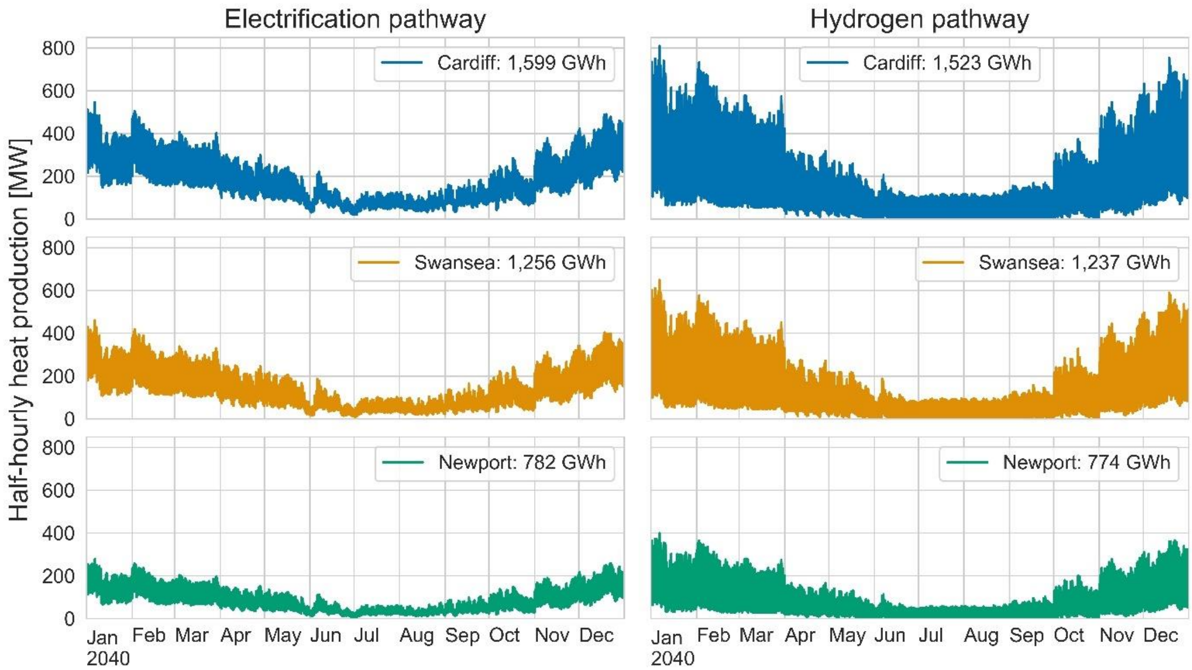


Figure E-6: Aggregated half-hourly heat production profiles of Cardiff, Swansea and Newport in 2040 for the electrification and hydrogen pathways.

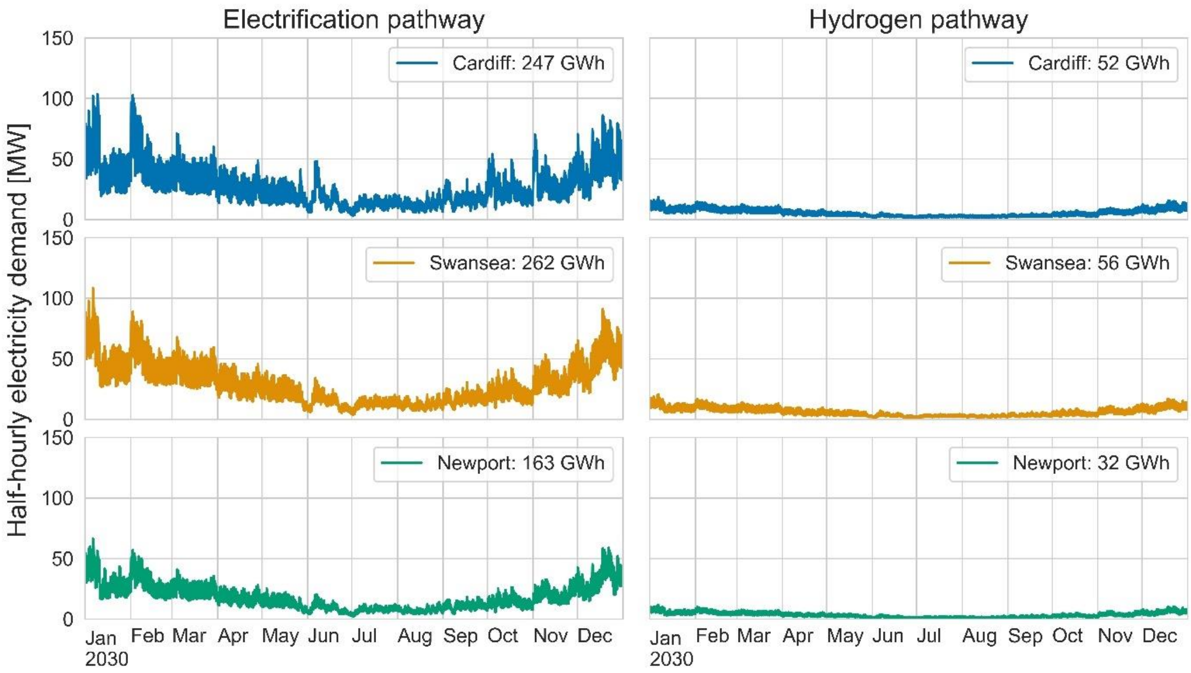


Figure E-7: Aggregated half-hourly electricity for heat profiles of Cardiff, Swansea and Newport in 2030 for the electrification and hydrogen pathways.

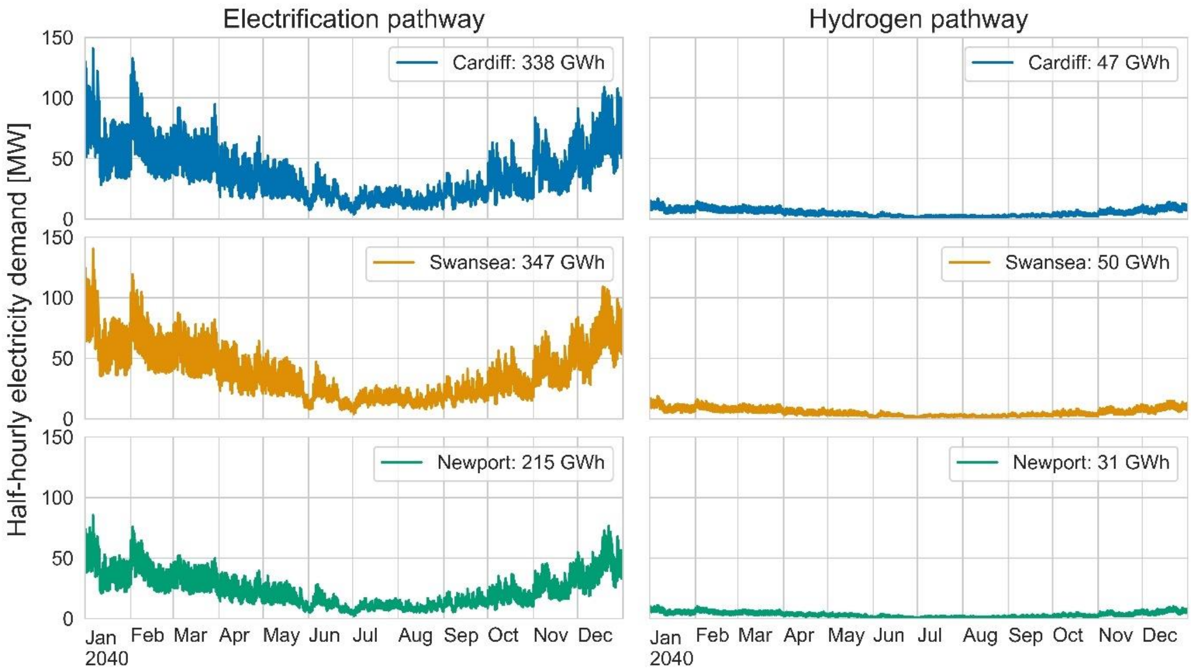


Figure E-8: Aggregated half-hourly electricity for heat profiles of Cardiff, Swansea and Newport in 2040 for the electrification and hydrogen pathways.

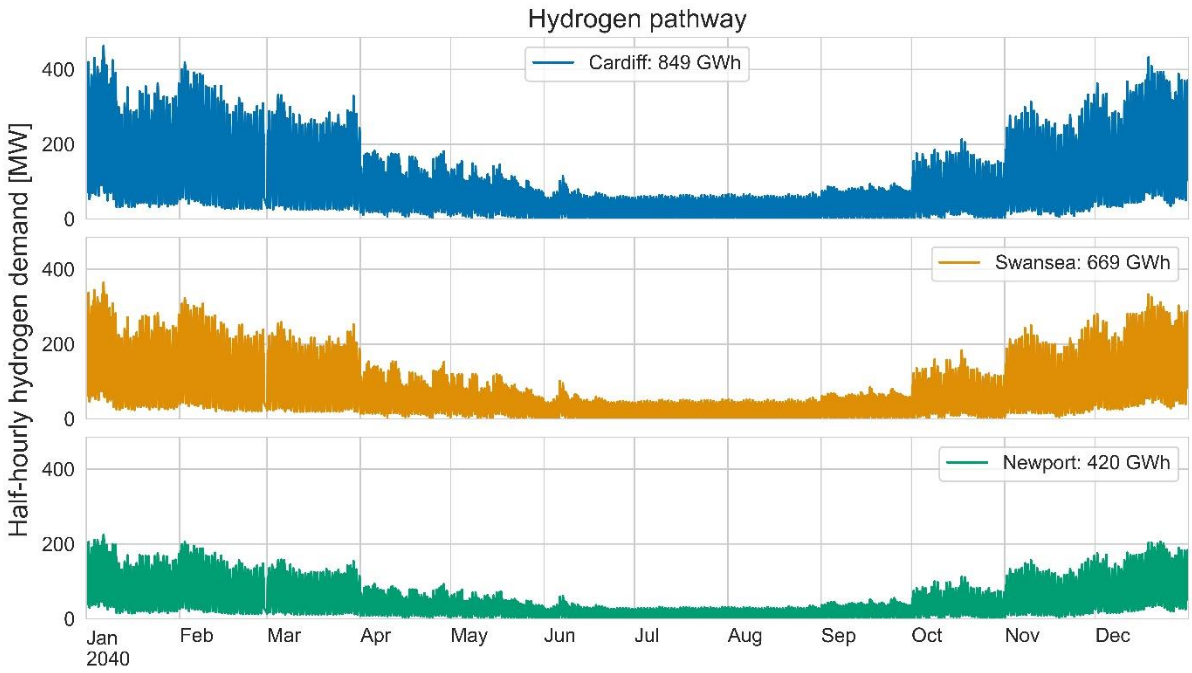


Figure E- 9: Aggregated half-hourly hydrogen for heat profiles of Cardiff, Swansea and Newport in 2040 for the electrification and hydrogen pathways.

E.3 Peak Electricity Demand from Substations in Swansea and Newport

The figures below show the peak electricity for heat demand in the substations of Swansea and Newport for the electrification and hydrogen pathways.

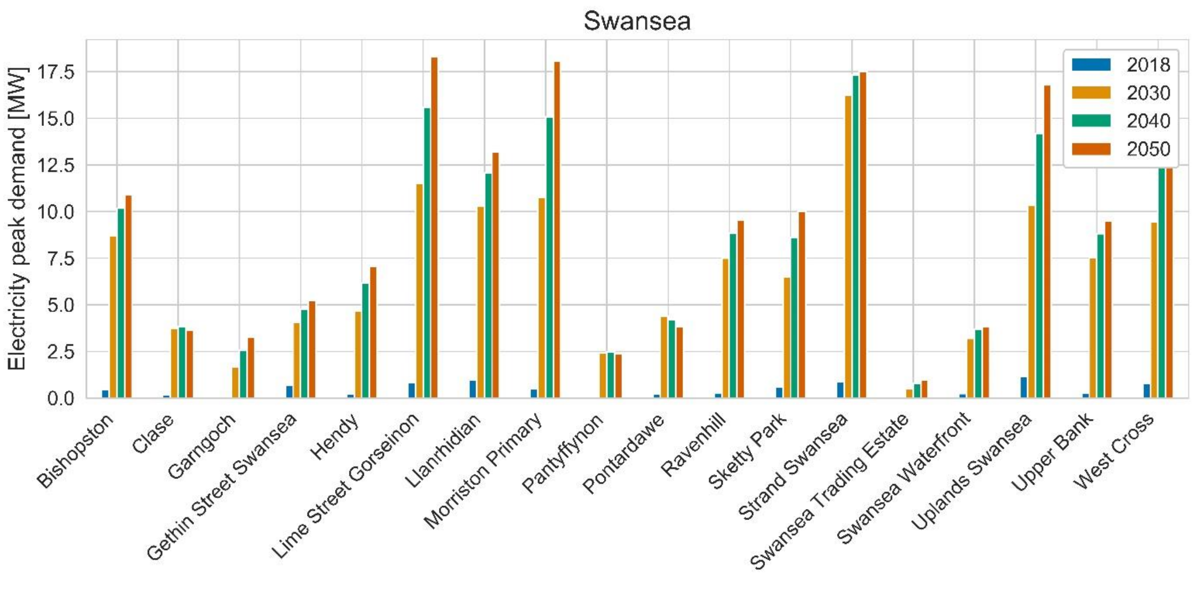


Figure E-10: Peak electricity for heat demand in the electrification pathway for Swansea

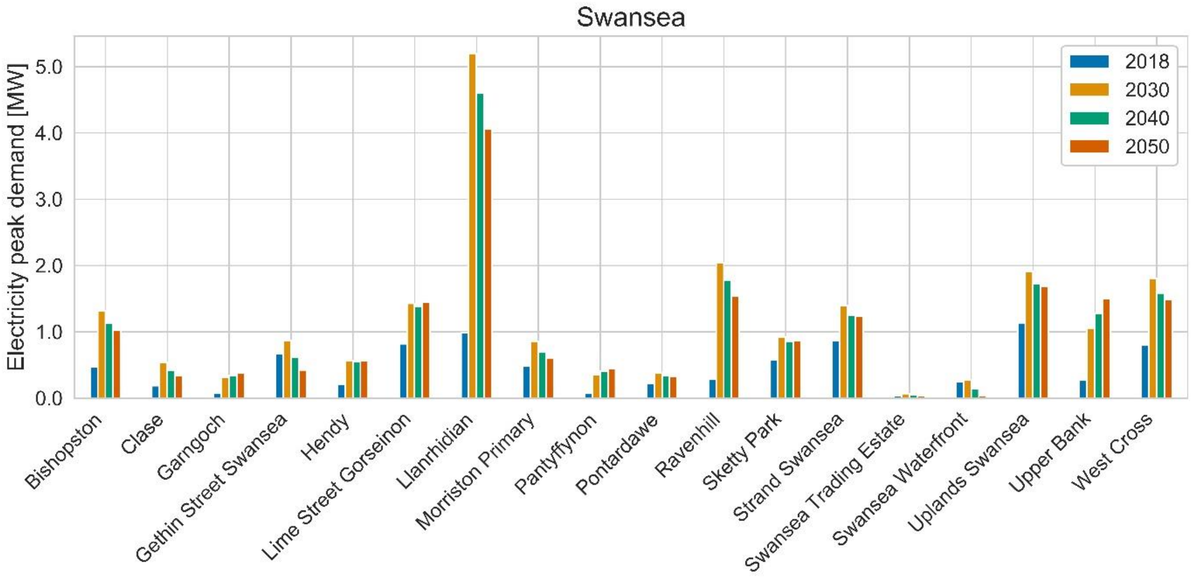


Figure E-11: Peak electricity for heat demand in the hydrogen pathway for Swansea

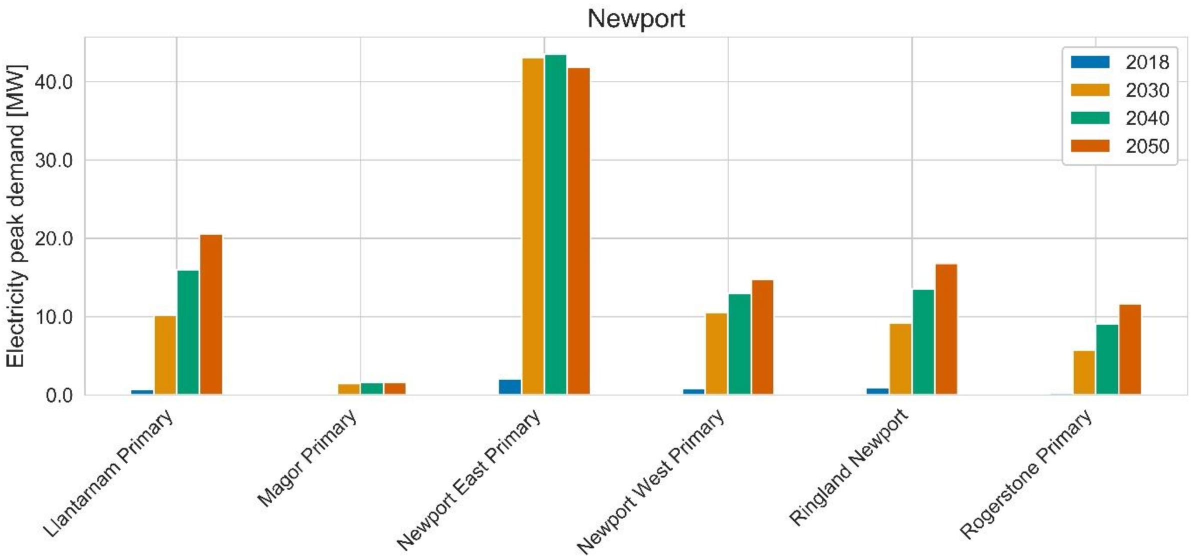


Figure E-12: Peak electricity for heat demand in the electrification pathway for Newport

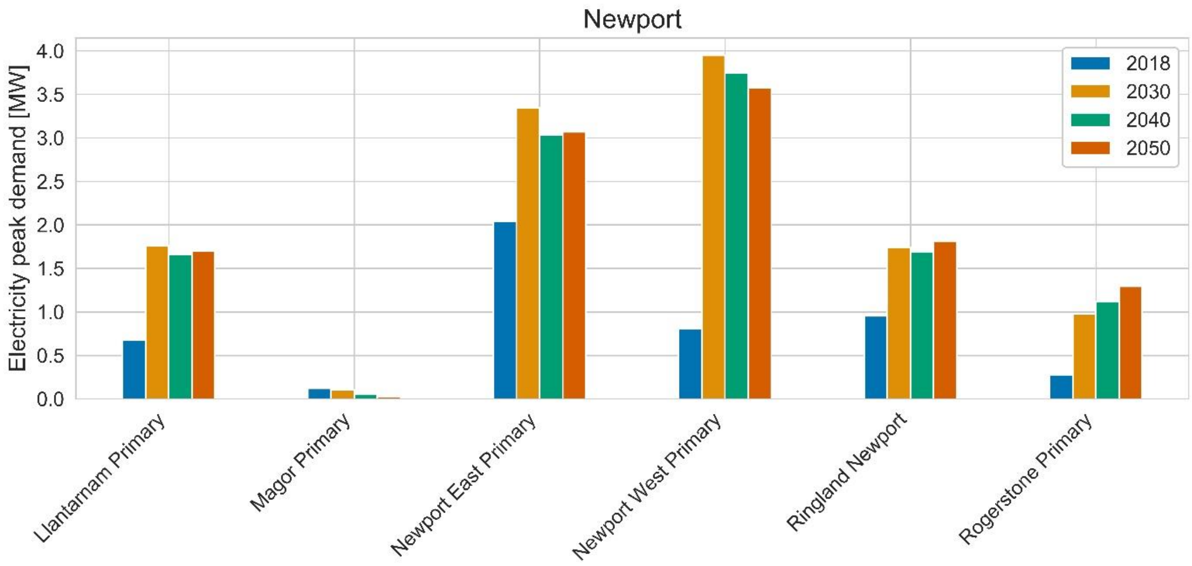


Figure E-13: Peak electricity for heat demand in the hydrogen pathway for Newport.

Appendix F Input Data for the Neath Port Talbot Example.

F.1 Heat Load Duration Curve in a Local Area in the UK

A heat load duration curve was built for each LSOA by using the heat demand profile from gas boilers and the estimated domestic heat demand. Currently, gas boilers are the main source of heat in NPT, thus the half-hourly consumption profile of a pool of gas boilers gives a good estimate of the heat demand profile. The Energy Demand Research Project [63] published gas consumption at half-hourly resolution for 14,000 households from early 2008 to the end of 2010. The hourly heat load duration curve was derived from this data by aggregating and averaging the heat demand for each timestep of a dataset containing data for the 14,000 households. It was then scaled based on the estimated domestic heat demand of the LSOA.

F.2 Assumptions Regarding the Connection to the Gas Network of the Different Dwelling Categories

When looking at a change or an upgrade of heating systems, knowing if a dwelling is connected to the gas grid can influence the final decision. A dataset published by BEIS provides information regarding the number of dwellings connected to the gas network at LSOA level [120]. However, there is no direct link between the dwelling category defined and their connection to the gas grid. For instance, flats equipped with gas boilers are connected to the gas network but flats using resistance heaters may or may not be connected. Hence, a few assumptions have been made:

- All dwellings using oil/solid fuel boilers are not connected to the gas grid.
- All detached dwellings using resistance heating are not connected to the gas grid.
- The rest of the dwellings connected to the gas network are proportionally distributed between semi-detached dwellings, terraced dwellings and flats using resistance heating.

F.3 Calculation of Linear Heat Density by LSOA

The linear heat density was estimated for each LSOA by using the length of the local road network[18] as a proxy of the length of a hypothetical heat distribution network.

F.4 Assumptions and Input Parameters to the Optimisation Model

Table F-1 shows the sources of the values and sources of the data used in the optimisation model.

Table F-1: Characteristics regarding fuel emissions, reinforcements of the electricity grid and investment

Parameters	Values	Source
Incentives	See source	Domestic RHI 2018. No incentives for district heating were considered.
Fuel emissions	See source	https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2018
Cost for reinforcement of the electricity grid £/kWh	227 £/kW peak over 30 years	https://www.enwl.co.uk/globalassets/innovation/enwl001-demand-scenarios--atlas/enwl001-closedown-report/appendix-2---delta-ee---managing-future-network-impact-of-electrification-of-heat.pdf for the reference scenario
ADMD for ASHP, GSHP and resistance heating	1.7, 1.7 and 3.4	ASHP and GSHP: [45] Resistance heating: https://www.enwl.co.uk/globalassets/get-connected/cic/icpsidnos/g81-library/1---design--planning/5-design--planning/code-of-practice-226--lv-network-design.pdf
Discount rate	4%	

[18] Road network data© Crown copyright and database rights 2018 Ordnance Survey (100025252)

The costs and characteristics associated with the individual heating technology are shown in Table F-2 and Table F-3. Decommissioning costs are added to the investment costs to the new heating unit when relevant. For instance, the replacement of a gas boiler by a resistance heating system requires the decommissioning of a gas boiler, which is estimated at £500, and the addition of hot water storage, which is estimated at £1,000. This would increase the investment cost from £1,500 to £3,000 for a flat. HHPs are considered to supply 80% of the heating using a heat pump and 20% using a gas boiler.

Table F-2: Costs and technical parameters of individual technology [31], [32] and [7]

Technology	Dwelling type	Capex [£/unit]	Fixed O&M (excluding elecricity) [£/year]	Technical lifetime [years]	Auxiliary electricity consumption [kWh/year]	Efficiency heat	Main fuel
Gas boiler	Flat	2000	75	20	150	84%	Ngas
Gas boiler	Detached	4000	75	20	150	84%	Ngas
Gas boiler	Semi-detached	2650	75	20	150	84%	Ngas
Gas boiler	Terraced	2650	75	20	150	84%	Ngas
Resistance heating	Flat	1500	21	30	0	100%	Electricity
Resistance heating	Detached	3150	25	30	0	100%	Electricity
Resistance heating	Semi-detached	2024	21	30	0	100%	Electricity
Resistance heating	Terraced	2024	21	30	0	100%	Electricity
ASHP air-water	Detached	8272	60	18	100	340%	Electricity
ASHP air-water	Semi-detached	7238	48	18	100	340%	Electricity
ASHP air-water	Terraced	7238	48	18	100	340%	Electricity
GSHP Borehole	Detached	13916	85	20	100	337%	Electricity
GSHP Borehole	Semi-detached	13200	85	20	100	380%	Electricity
Oil boiler	Flat	3100	100	20	140	84%	Oil

Technology	Dwelling type	Capex [£/unit]	Fixed O&M (excluding elecricity) [£/year]	Technical lifetime [years]	Auxiliary electricity consumption [kWh/year]	Efficiency heat	Main fuel
Oil boiler	Detached	5192	205.92	20	140	84%	Oil
Oil boiler	Semi-detached	3100	100	20	140	84%	Oil
Oil boiler	Terraced	3100	100	20	140	84%	Oil
Biomass boiler	Detached	5984	429.44	20	240	82%	Biomass
Biomass boiler	Semi-detached	5984	429.44	20	240	82%	Biomass
Biomass boiler	Terraced	5984	429.44	20	240	82%	Biomass
Biomass boiler	Flat	5984	429.44	20	240	82%	Biomass
Hybrid HP	Detached	7333	96	12	110	289%	Hybrid
Hybrid HP	Semi-detached	7333	96	12	110	289%	Hybrid
Hybrid HP	Terraced	7333	106	12	110	289%	Hybrid

Table F-3: Decommissioning costs table [7] and the "Hertfordshire Renewable and Low Carbon Energy Technical Study" from AECOM

Action	EAC [£]	Cost [£]
decommission/replacement boiler	45	500
Replace/ upgrade / decommission (wet) heat emitters	36	400
District heating substation House	462	7218
District heating substation Flat	296	4621
Hot water storage	90	1000

The costs related to the production of heat for district heating are shown in Table F-4. The assumption for the feed-in tariff for electricity is that CHPs can sell electricity at a rate 30% lower than the retail price.

Table F-4: Costs and technical parameters of heat supply technology for district heating [34] and [22].

Technology	Lifetime [years]	Specific CAPEX [£/MW]	Fixed OPEX [£/MW/year]	Variable OPEX [£/MWh]	Efficiency heat	Efficiency electricity
Natural gas boiler	25	52,800	1716	0.88	97%	0
Heat pump	25	616,000	1760	1.584	500%	0
Natural gas CHP unit	25	889,778	25784	3.872	45%	35%