Characterising Network Asset Uncertainty on Distribution Networks

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Abstract

The integration of domestic electric heat pumps at LV (low-voltage) level forms a key component of the UK's heat and buildings decarbonisation strategy. However, the traditional constraints of distribution power networks – limited communication and control, with low system visibility – imposes several challenges when attempting to quantify future network impacts of increased heat pump adoption at LV level. Electrical heat load is sensitive not only to temperature, but locally variable parameters such as building construction and occupant demographics. This work builds on previous research by developing novel methodologies for the localisation of electrical heat load from trial and operational data augmented by supplemental datasets, overcoming the limitations of using pure trial data when aiming to quantify local electrical heat load and consequent network effects. This addresses the need to quantify potential LV network impacts in the absence of complete data and enhances the potential observability of distribution network assets without the need for investment in additional monitoring hardware.

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Glossary of Terms

ADMD	After Diversity Maximum Demand
ASHP	Air Source Heat Pump
AWS	Amazon Web Services
BAU	Business as Usual
BEIS	Department for Business, Energy & Industrial Strategy
CCC	Climate Change Committee
CEDA	Centre for Environmental Data Analysis
CHP	Combined Heat and Power
COP	Coefficient of Performance
DNO	Distribution Network Operator
DSO	Distribution System Operator
EDRP	Energy Demand Research Project
EHP	Electrical Heat Pump
EPC	Energy Performance Certificate

EV	Electric Vehicle
FES	Future Energy Scenarios
GB	Great Britain
GHG	Greenhouse Gas
GIS	Geographic Information System
GSHP	Ground Source Heat Pump
HP	Heat Pump
IPCC	Intergovernmental Panel on Climate Change
kWh	kilowatt-hour
LAEP	Local Area Energy Planning
LCL	Low Carbon London
LCT	Low-carbon Technologies
LV	Low Voltage
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MIDAS	Met Office Integrated Data Archive System
NIALM	Nonintrusive Appliance Load Monitoring
Ofgem	Office of Gas and Electricity Markets
PV	Photovoltaic

RHI	Renewable Heat Incentive
RHPP	Renewable Heat Premium Payment
RMSE	Root Mean Squared Error
SIMD	Scottish Index of Multiple Deprivation
UKPN	UK Power Networks
WMAPE	Weighted Mean Absolute Percentage Error

Chapter 1

Introduction

1.1 Overview

The ambitious decarbonisation targets set to achieve Net Zero by 2050 in the UK demands change to the Great Britain (GB) energy system at a rate and scale that is unprecedented in recent history. At present, there are many policy, technical and sociological barriers to achieving target heat pump uptake within the UK that will act as headwinds with respect to achieving target levels. In a power networks context, the rapid connection of new low carbon technologies at the low voltage (LV) level - both generation and load types - necessitate new tools and methodologies for network planning, design and decision making. Within the UK, the LV network facilitates the last-mile of electricity distribution to end-users at 240V [1].

The aggressive push to electrify domestic heating presents many specific technical challenges in terms of how additional load can be accommodated on existing networks whilst optimising investment and minimising physical intervention. In the presence of ongoing uncertainty surrounding which decarbonisation pathways will become dominant, non-network solutions which minimise physical network interventions become particularly attractive for utilities.

The principal challenges for distribution network operators can broadly categorised as uncertainty surrounding future electrical heat pump uptake, and uncertainty surrounding how specific penetrations of electrical heat pump will impact distribution network assets in terms of voltage and current effects. Combined, the uncertainty surrounding penetration levels and the corresponding shape and time of use characteristics of electrical heat load must be managed by distribution network operators' (DNO's) seeking to optimise investment and maintain security of supply to customers.

As an alternative to physical models, data-driven solutions are currently widespread for power systems applications. This approach is particularly attractive for power distribution networks which feature low levels of visibility, communication, and control in combination with a very high number of physical assets. However, maximising the value of data-derived insights poses an additional series of challenges.

In order to quantify the network voltage and current impacts of increased electrical heat pump penetration, there have been numerous trials undertaken within the UK [2] [3] [4] in order to capture electrical heat load for households installed with electrical heat pumps. This serves to inform possible time of use patterns combined with electrical heat load magnitudes, however there are key limitations associated with trial data. Each trial captures electrical heat pump usage for a limited subset of customers for a specific geographic location and for a specific period of time. Unlike other low carbon technologies, such as wind and solar generation, or EVs, electrical heat load is sensitive to a range of parameters in addition to the rating of the hardware itself. Electrical heat load is proportional to the physical characteristics of the household being heated, in addition to the thermal comfort and occupancy routines of the household occupants. The geospatial variance in these parameters serves to introduce a delta between trial data results and potential network impacts in a target area.

Corresponding with limited availability of trial data, there is presently a significant gap between the number of households fitted with electric heat pumps, and the levels necessary in order to achieve decarbonisation. For the modelled Further Ambition scenario, the CCC recommends the installation of 19 million heat pumps [5] At the 2019 installation rate of 1.5 installations per 1000 households [6], this would take 700 years to achieve. Therefore, there is additionally a very limited availability of operational electric heat pump data to draw on to inform future network effects.

The limitations of data availability for facilitating the uptake of low-carbon technology at the LV level has been highlighted by [7]. These limitations are systemic and are likely to remain in place for the near future. The cost and effort of implementing trials alongside with the low operational observability of LV networks, combined with the legal obligation for data anonymisation means that load data is typically highly aggregated or lacking in geospatial context. Localisation of electrical heat load impacts for LV networks in the presence of limited trial data and operational data then becomes a key issue. Due to the scale of the aggregated UK distribution network – over 500,000 substations and millions of kilometres of cabling – any localisation approach must be sufficiently robust to work over a range of areas.

This work seeks to develop novel data-driven methodologies to reduce the uncertainty surrounding the bulk network voltage and current effects due to the increase of increased electrical heat pump penetration at LV level. This thesis therefore proposes a novel electrical heat load model that draws load magnitude and shape information from existing trial datasets, with further scale localisation through the use of geospatially linked supplementary datasets to better inform future electrical heat load across the entire power distribution network of the UK. This overcomes the limitations of standalone trial data as highlighted previously in [8] , where trial data only provides average or indicative results and can lack translatability from the area of original data capture. A series of case studies using the developed methodologies are used to demonstrate the effects of load localisation. This thesis demonstrates how findings from costly trial data can be augmented in order to extract improved insights and minimise the need for additional investment in monitoring or physical network intervention. Whilst this work focuses on electrical heat load modelling, these concepts similarly apply in an LV networks context for other low-carbon technologies such as EV's and distributed generation, where limited trial data forms core insights for prediction of LV network impacts at increased penetration.

1.2 Principal research contributions

The contributions of this thesis are summarised as follows:

- A novel probabilistic electrical heat load relation model is developed from trial datasets, building on previous works which have focused on modelling highly aggregated heat pump load at winter extremes rather than across the entire range of temperature conditions. This methodology is sensitive to local ambient temperature as well as number of customers.
- A novel localisation electrical heat load model is developed, overcoming the limitations of highly aggregated electrical heat load profiles in order to develop load profiles that are sensitive to geospatially variable factors such as building physical parameters and individual demographics. The impact of localisation is demonstrated via calculation of localised after diversity maximum demand (ADMD) and through a feeder case study.
- A new approach for disaggregation of electrical heat load from aggregated LV transformer load data is demonstrated, facilitating the extraction of electrical heat load from existing LV sensors without the need for additional monitoring capability. This improves network situational awareness with respect to electrical heat load.
- A unified methodology incorporating previously developed electrical heat load models combined with the electrical load disaggregation methodology in order to augment locally extracted data and provide feeder specific insights. This overcomes the limitations of static models which are dependent on standalone trial data.

1.3 Thesis Outline

This thesis is dedicated to enhancing the modelling and localization of electrical heat load amidst the UK's drive towards heat electrification. Initially, it establishes the contextual backdrop and reviews existing methodologies, followed by the introduction of the proposed approach, which includes data-driven heat load prediction, geospatial localization, and electrical load disaggregation. The structure of the thesis is presented below:

Chapter 2 reviews the context for the electrification of heat within the UK, provides an overview of uncertainty in a distribution networks context and presents a general overview of existing research in this problem area.

Chapter 3 develops a novel data-driven approach for predicting future electrical heat load shapes in the absence of detailed metadata, sensitive to local temperature conditions and number of customers. This builds on previous approaches for modelling increased domestic heat pump at the LV level, which incorporate only worst-case extremes rather than temperature sensitive approaches.

Chapter 4 presents a methodology for the localisation of the electrical heat load shapes developed in Chapter 3, whereby the effects of geospatially variable physical and demographic effects are incorporated into the final electrical network load. This contributes another development beyond using standalone trial data without localisation of building and demographic effects.

Chapter 5 proposes a novel disaggregation of electrical heat load from aggregated LV transformer load, facilitating the extraction of electrical heat load from existing LV sensors without the need for additional monitoring capability. This couples the load and time of use insights provided by existing trial data, with geospatially sensitive heat localisation for the specific LV feeder. This provides a methodology for extracting locally specific heat load without the need for additional network monitoring, that can be coupled with the heat models presented in Chapters 3 and 4

Chapter 6 unifies the contributions into an end-to-end demonstration of the developed electrical heat load models, combined with the electrical heat load disaggregation used together in order to augment local load data which may be limited, poor quality and incomplete.

Chapter 7 summarises the contributions and the implementation of the research. Furthermore, future work, such as developing associated measurement devices and a data processing platform, are discussed.

1.4 Publications

Journal papers:

- Predictive thermal relation model for synthesising low carbon heating loads profiles on distribution networks, A. Anderson, B. Stephen, R. Telford, S. D. J. McArthur, *IEEE Access*, PP(99):1-1, October 2020
- Scaling of Localised Electrical Heat Demand for LV Distribution Networks Using Geospatially Linked Gas Demand Data, A. Anderson, C. McGarry, B. Stephen, S. D. J. McArthur, *Applied Energy, 2023* [Under Review]
- A scalable geospatial data-driven localisation approach for modelling of LV distribution networks and multi-LCT impact assessment, C. McGarry, A. Anderson, I. Elders, S. Galloway, *Applied Energy, 2023* [Under Review]

Conference papers:

- A probabilistic model for characteristic heat pump electrical demand versus temperature A. Anderson, B. Stephen, R. Telford, S. D. J. McArthur, The 2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), Den Haag, Netherlands, 2020
- Multi Vector Energy Demand Modelling for Predicting Future Low Carbon Heat Loads A. Anderson, B. Stephen, S. D. J. McArthur, The 2022 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), Novi Sad, Serbia, 2022

Chapter 2

Background and The State-of-The-Art for Low Carbon Heat Load Modelling

This chapter presents the wider contextual background for the motivations behind this research project, outlines the technical context surrounding load uncertainty at LV level and reviews the current state of the art with respect to electrical heat load modelling and uncertainty management for network operators. Ongoing industry projects and the current capabilities of DNO's are outlined.

2.1 Background

In recent years, climate change has been established as the greatest single threat faced by humanity and global ecosystems [9]. In their latest report, the IPCC (Intergovernmental Panel on Climate Change) state is that it is now unequivocal that humanity's greenhouse gas emissions are linked to more-frequent, more intense extreme weather events [10], with serious consequences for international economic, political and societal stability.

The modern age has seen the effects of human-induced climate change shift towards both increased geographic scale and increased severity. The air pollution of the Industrial Revolution in the 19th century contributed to a massive increase in respiratory disease and increased mortality in factory towns as well as surrounding areas [11]. In the US the Dust Bowl of the 1930s, caused by over intensive farming, resulted in drought and erosion over an area of 100,000,000 acres. Over 500,000 individuals were left homeless as the affected area become uninhabitable, and a further 3.5 million people were displaced. More recently, extreme winter storms in Texas in February of 2021 caused the worst energy infrastructure failure in Texas state history, leading to shortages of water, food and heat for 4.5 million homes due to unprecedented weather conditions [12].

Today, the tangible effects of climate change are not constrained to individual cities, regions, or even continents. The six years leading up to 2021 were the hottest years on record, and 2021 itself saw over 400 weather stations around the world beat their all-time highest records. Rises in sea levels contributed by ice-mass loss and thermal expansion of the ocean [13] encroach on coastal areas, with up to 630 million people presently living below the modelled 2100 flood levels [14]. Ongoing environmental destruction through man-made processes has resulted in a global species loss of 68% in less than 50 years, signalling an ongoing loss of biodiversity that threatens to collapse already fragile ecosystems. [15].

The impact of human-induced climate change therefore now presents an existential threat to humanity, with profound implications for international relations, resource security and quality of life for individuals living today as well future generations.

A challenge of this scale necessitates a global response, and recent years have seen increasing levels of awareness and cooperation between nations in attempt to mitigate the effects of climate change. The Kyoto Protocols adopted in 1997 was ultimately ratified by 192 countries, representing the first time binding GHG (greenhouse gas) reduction targets were set for industrialised countries. Whilst not a total success (partially derailed by the US refusing to participate), it is estimated that the Kyoto Protocols resulted in an emissions reduction of 7% compared to no action being taken [16]. Further to this, in 2015 the Paris Agreement was ratified. This treaty formally recognised the requirement to reduce the increase in to well below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change [17].

In turn, these international efforts drive policy decisions and long-term government strategy at the national level. Within the UK, the 2008 Climate Change Act made the legal commitment to ensure that net UK carbon accounts for all six Kyoto greenhouse gases for the year 2050 were at least 100% lower than the 1990 baseline [18]. As of 2019, the UK became the first major economy to make a legally binding commitment to net-zero greenhouse gas emissions by 2050 [18]. Reducing emissions to target levels necessitates a multi-faceted approach that encompasses the decarbonisation of multiple sectors including industry, transportation and agriculture as well as the power system as a whole. This will ultimately require technological innovation and adaptation from industry, academia, regulators and government, as well as behavioural shifts within society as a whole.

It is against this backdrop of increasing political commitment to carbon emissions reduction that the UK's energy sector is facing a time of unprecedented change. Supported by the falling cost of photovoltaic technology and government subsidies, solar generation has grown from zero to over 13.5MW of capacity in the last ten years alone [19] . Along similar lines, wind generation has grown from contributing 1% of the UK's electricity use in 2008 to 24.8% in 2020 [20], having surpassed coal in 2016 and nuclear in 2018 [21]. This was supported in part by the Renewables Obligation (RO), designed to encourage generation of electricity from eligible renewable sources in the UK. In tandem with the increasing proportion low-carbon generation, in 2015 UK coal usage fell to the lowest level seen since mid 19th century [22]. In 2012, coal accounted for 40% of the UK's power generation and had collapsed dramatically to only 1.8% in 2020 [21].

Whilst significant gains have been main regarding the decarbonisation of generation in the UK, significant further effort remains in order to reduce the carbon emissions of other sectors. In 2021, more than 60% of power generation came from low-carbon sources [21], whereas less than 5% of total buildings heat demand in the UK came from low-carbon sources [23]. Therefore, in comparison to the generation sector, the decarbonisation of the UK's heat and transport sectors are currently in their early stages compared to the UK's long term strategic ambitions. National Grid Future Energy Scenarios (FES) suggest that the UK's stock of EV's could reach between 2.7 and 10.6 million by 2030 and as high as 36 million by 2040 [21].

Unconstrained, the National Grid estimates this could contribute an additional 19GW of demand through electric-vehicle (EV) charging by 2040 [21]. Similarly, for the heating sector, existing GB winter peak heat demand is estimated to be approximately 170GW [24]; more than double when contrasted with the current network electricity peak demand of 59.GW [25].

Shifting this gas demand to the electricity network within the necessary time frames poses an enormous effort for the UK's energy system, especially when considering the broader context of decarbonisation. The transfer of energy of these sectors from fossil fuel-based systems to fully electrified sectors will significantly alter the UK's aggregate energy demand, as well as modify patterns of energy consumption at the household and consequently LV asset level.

2.1.1 Decarbonisation of Heat

The decarbonisation of heat in the UK forms one of the main, and arguably the most difficult [26], obstacles to achieving the country's Net Zero targets by 2050. At present, heating accounts for over a third of the UK's greenhouse gas emissions [27], most of this heat being supplied by fossil fuel derived natural gas. These emissions are jointly contributed by domestic space heating, hot water and cooking usage as well as industrial processes. Representing 0.87% of the world's population, the UK consumes 2% of the world's total natural gas consumption [28]. The UK's outsized reliance on natural gas is a reflection of multiple factors; high levels of industrialisation and development and a cold winter climate combined with historically low gas prices and the comparatively low upfront costs and efficiency of gas boilers [26]. The discovery of natural gas deposits in the North Sea in the 1960s kick-started the transition away from town gas to natural gas for heating within the UK, supported heavily through government-led programmes [29]. By 1999, during the peak of UK North Sea natural gas production, natural gas accounted for 40% of the UK's total inland energy consumption [21].

At present 23 million households, or 85%, of residential buildings in the UK use gas-fired boilers to meet domestic heating requirements [30]. This is in contrast with other nations in Western Europe where there is less reliance on gas for central heating; in Germany only 50% of homes are heated with natural gas [31] , and similarly in France, 35% of homes are heated with natural gas [32]. Alongside the heavy reliance on natural gas for domestic heating, UK housing stock represents one of the oldest and in Europe, with only around 15% of existing stock built since 1990 [33] and a UK home's average gas consumption over double the EU average [34]. As well as reducing building heating efficiency, this has negative consequences for quality of life; in 2007, the Royal Commission on Environmental Pollution concluded that even in the 21st century, cold was the main factor underlying the UK's higher annual death rate between December and March [35], with vulnerable groups such as older people and young children at particular risk [36].

The decarbonisation of heat in the UK is contingent on a series of different measures to achieve reduction of carbon emissions generated from the UK's heating sector to target levels. The CCC defines the main decarbonisation solutions for UK homes as: (i) heat pumps, (ii) hydrogen and (iii) heat networks, alongside the complementary work of increasing energy efficiency through improved insulation [23]. These low-carbon heating technologies exist in contrast to existing conventional heating technologies, such as gas boilers and oil-fired heaters, which are dependent on fossil fuels as a means of heat generation.

The electrification, and subsequent decarbonisation of heating, through conversion of fossil-fuel fired heating to electric heat pumps forms one key aspect of the UK's overall heat decarbonisation strategy. The suitability of specific low-carbon heating solutions will be dependent on existing constraints of the housing stock, as well as existing heating system and feasibility of retrofitting for different low-carbon heating types. The CCC projects that by 2050, 52% of homes will be heated by heat pumps, 42% by district heating, 5% by hydrogen boilers and a further 1% by alternative sources [37]. Therefore whilst there is no single solution for the decarbonisation of heat within the UK, heat pumps will form a key component of achieving target emissions reductions.

Domestic heating lies at the convergence of many economic and societal issues, whilst also being a core component of the UK government's decarbonisation strategy, as well having a fundamental impact on individual day to day wellbeing and comfort. In order to meet Net Zero, virtually all heat in buildings will need to be decarbonised [38]. It is anticipated that this will be achieved through a range of measures, encompassing energy efficiency improvements, hydrogen and bioenergy solutions as well as further adoption of electric heat pump technology. A transformation of this scale necessitates the strategic input of industry and government at the highest level, as well as support from grassroots organisations, small businesses and local authorities. This represents a complex interplay of dependencies and institutional cooperation, and in this context, there remains significant uncertainty about how the decarbonisation of heat will evolve in both the short and long term.

2.1.2 Distribution Network Operators, Low Voltage Networks, and the Transition to Net Zero

As a result of the ongoing drive to Net Zero and decarbonisation of the UK economy, Distribution Network Operators (DNO's) find themselves at the forefront of facilitating the decarbonisation of the presently carbon intensive transport and heat sectors.

By their nature, the transformation of these sectors presents a difficult challenge in contrast to accommodating the transition of large-scale generation from fossil fuels to renewable sources. Large scale generation in the UK is managed by a comparatively small handful of commercial institutions, reducing the number of stakeholders and simplifying the process of change. Alongside this, large scale generation represent very high value assets and therefore there is corresponding capital investment in the upkeep, monitoring, and ongoing maintenance of these systems as well as planning for the future. Whether these systems are fossil fuel or renewables based has no material impact to the experience of the customer at the point of use.

In contrast, the UK's transport and heat sectors represent are intrinsically linked with the immediate needs and routines of almost every member of the population. Over 77% of UK households own a car [39] and 95% of households are equipped with central heating [40]. Decarbonisation of these sectors raises the potential for a world where a majority of individuals are reliant on their home's electricity supply for meeting their transportation and heating needs. This represents a radical shift in both the possible energy throughput on the distribution network, as well as the time of use and peak power characteristics of typical domestic customers. The increasing penetration of small-scale generation such as roof mounted solar panels [41] and domestic energy storage alongside EV's further increases the uncertainty surrounding future network conditions.

As the entity responsible for the electrical interface between the transmission network, and the distribution network up to the point of connection with a home, DNO's are therefore in the position of needing to facilitate this transformation through appropriate investment in infrastructure alongside technical guidance and policy support. Historically, DNO's have been responsible for the maintenance and upkeep of a largely passive infrastructure. The predictability of domestic consumption meant that network assets could be sized via simple metrics such as ADMD, with a fit and forget approach, where modelled voltage and thermal ratings could be anticipated to remain appropriate for the operational lifetime of the assets. Power flows could be assumed to be unidirectional due to the lack of LV-connected generation. As a result of this the physical distribution network of the present day is a reflection of the historical status quo; the power distribution network features very low levels of communication and control, with a corresponding poor level of observability. Geographic information systems (GIS) have improved some aspects of asset management, but in many cases the cable type was not recorded at the point of installation and is unknown even to the network operator [42].

Traditionally, the steps to design an LV network can be broken down into an evaluation of the total load requirement, an evaluation of the supply capacity of the existing network, followed by appropriate provision of substations, cable layout and sizing [43]. Cable sizing, or cross-sectional area design, will be driven by the aggregated ADMD estimated for the aggregated customer types served by a feeder. The network segment under design would be sized with sufficient headroom to accommodate worst-case scenarios with minimum intervention from the network operator [44]. Historically, users connected to 400V feeders have been consumers of energy, with unidirectional load, and load magnitude and growth stable over long time horizons.

The future electrical distribution network presents a more complex operational and planning challenge. The adoption of several new technologies stands to radically shift how households consume and use energy. The uptake of rooftop solar [45] in the UK means that on particularly sunny days, feeders with high rates of rooftop solar could result in reverse power flow from low-to-high voltage on a network. With insufficient load, this could result in voltage exceedances and therefore breach of upper voltage limits; a scenario not traditionally accounted for with the ADMD-driven design philosophy. The mainstream adoption of EV's and home lithium-ion batteries introduces an energy storage component to households that did not previously exist. Households with energy storage have the capability to source or sink power to a feeder. Energy storage could potentially be utilised in demand response type programs to help balance demand and supply, but unmanaged could result in significant amounts of low-diversity load being applied to a feeder such as during periods of overnight charging. Finally, the adoption of EHP's introduces a new electrical load that which has an energy consumption highly proportional to external air temperature. Whilst ADMD-sizing could be appropriate for rating assets subject to worst-case winter conditions, the inherent temperature dependency would result in underutilisation of network assets for most days where temperatures are not at winter extremes.

The electrical distribution network of the future therefore sees the transition of LV load-types from simple, unidirectional loads to a complex interplay of conventional load, stochastic generation, energy storage and temperature dependent electrical heat load. Conventional ADMD-sizing methodologies are still valid for LV network design, but simple application of an aggregated ADMD without taking into account the energy-mix on a feeder introduces the risk that a network will be under or oversized over its intended operational lifetime.

This increased complexity in energy consumption places additional pressure on DNO's to ensure that they maintain their obligation to their licence conditions in the presence of increasing planning and operational uncertainties.

In the UK DNO's are responsible for delivery of electricity to over 26.6 million homes and businesses [46] , covering a geographical area encompassing almost the entirety of the UK, along with corresponding switchgear, protection, and other associated devices. They provide the last mile of electricity to almost every home and business in the UK in both rural and urban settings. In part due to the passive nature of the distribution network, in the past DNO's have been institutionally inert with respect to technological change and innovation. In the aftermath of deregulation in the GB electricity sector in the early nineties, innovation spending fell to all-time lows, falling from £14m in 1990 to less than £1m in 2001 [47]. Thanks to various incentives and the introduction of matched innovation funding, DNO capital investment in innovation has recovered to pre-deregulation levels in recent years [48].

Decarbonisation necessitates the transformation of DNO's from passive industry incumbents to active participants in a rapidly evolving technological landscape, responsible for engaging with market participants, and active management of network assets. Alongside investment in innovation and development of new hardware solutions, DNO's must be equipped with the appropriate skills at every level of their business in order to support the integration of low carbon technology as cost effectively as possible without compromising quality or security of service.

2.2 Distribution Network Load Uncertainty

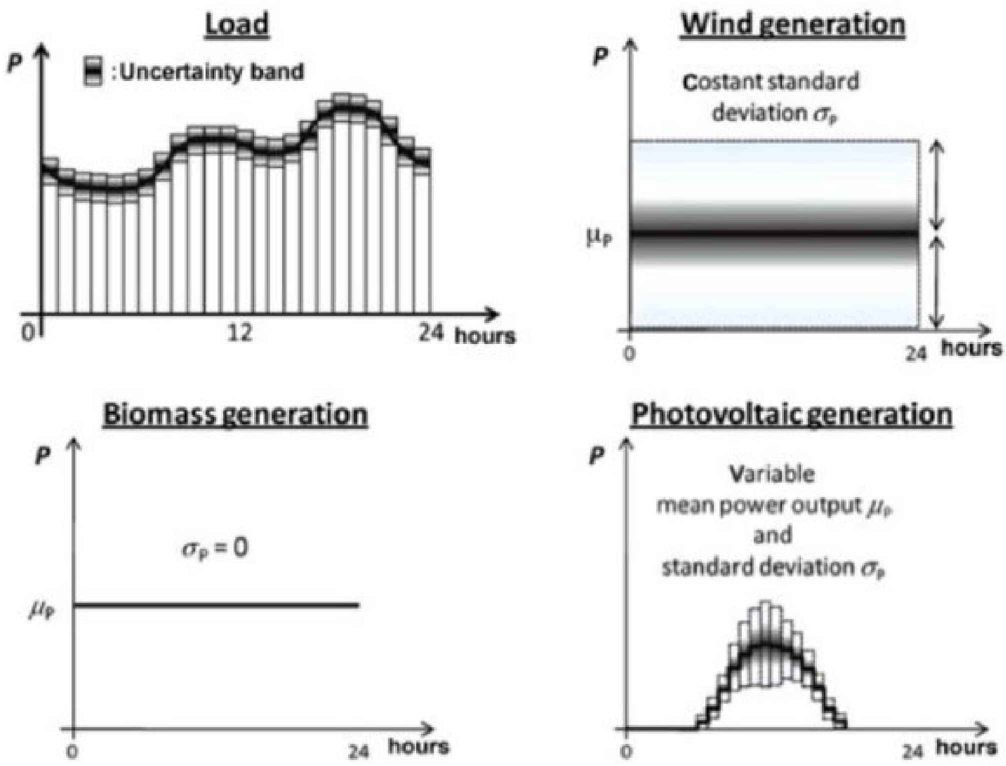


Figure 2-1 Load and generation modelling suitable for active distribution network planning with high shares of renewable energy systems, reproduced from [49]

Uncertainty is a component of any complex system as well as being part of everyday life. It is a fact that even for a simple system, it is not possible to have perfect knowledge of all system conditions and therefore the relationship between system inputs and outputs. In practice, there is generally a trade off between the cost to appropriately monitor a system and the need to actually do so [50]. Therefore, uncertainty arises from the need to infer possible outcomes or operating conditions from limited input data.

The GB power system is in a continuously evolving state, with generation and load shifting moment by moment through the combined actions of literally millions of independent actors. In addition to being in a constant state of change, even network operators do not have full visibility of the systems they manage. Distribution network operators typically have limited real time and historical visibility of network conditions. Whilst 11kV substations will feature some level of monitoring, most day-to-day operations on 415V LV feeders will occur with no external monitoring or human intervention until a fault is reported. Whilst potentially featuring hundreds of elements and customers in a single distribution network area, the potential complexity of the power system at the distribution level has historically been offset by the low uncertainty associated with LV-connected load types.

Accommodating new load types at the LV network level poses one of the fundamental problems on the path to decarbonisation for DNOs. These low-carbon technologies include battery-based technologies such as energy storage and electric vehicles, as well as small-scale generation capabilities including solar photovoltaic systems and wind turbines. Battery-based solutions are capable of both charging and discharging via the electricity grid. Generation in the electricity network has conventionally flowed from high-voltage to low-voltage, but small-scale wind and solar generation presents the possibility that conventional load flows can be reversed at times of high generation.

In the presence of an uncertain future, how can low carbon technologies be maximally facilitated, accommodated, and optimally managed whilst remaining cost effective? DNO's are responsible for ensuring that network infrastructure remains fit for purpose and mandated by their licence conditions to ensure that voltage and thermal limits remain sufficient in order to accommodate continuing quality of service to customers. Unlike traditional LV-connected loads which historically have been highly predictable over long periods of time, the contribution of low carbon load types can vary greatly depending on local weather conditions or behavioural routines. Non-network solutions that facilitate demand management through intelligent load shifting or other techniques are particularly attractive for DNO's as these solutions can defer the need for costly physical reinforcement until the development of more dominant technologies becomes clearer.

The combined lack of observability combined with new low carbon load and generation types creates an opportunity for the application of data-driven techniques, including machine learning methods, which can support decision making in the absence of complete information in order to support network decision making given the unique constraints of LV network applications.

Conventionally, monitoring is only available at the point of the LV transformer, typically with 30 minute resolution at best due to the half-hourly settlement periods of the electricity markets [51], and often subject to poor or low quality data [52]. Each LV transformer can be responsible for supplying electricity on the order of tens to hundreds of households, and therefore whilst the aggregate voltage and current characteristics can be known, the underlying contributions from each household and their corresponding dependencies are not visible.

Load modelling comprises a range of functions for DNOs and associated stakeholders. It is primarily of interest to be able to appropriately predict future LV loads with sufficiently robust confidence such that network operators as well as other stakeholders can be supported with making intelligent, cost-effective decisions for future network development.

The advent of LV-connected low-carbon technologies over a relatively short span of time stands to rapidly alter conventional load profiles, with corresponding threats to voltage and thermal limits. As previously discussed, the electrification of heat and transport will be fundamentally reliant on shifting demand from fossil fuel-based systems to the electricity network [27] [53]. Domestic applications such as space heating, cooking and hot water contributed 26% of all UK CO_2 emissions in 2016 [27]. It can therefore be implied that in order to decarbonise heat, significant changes must be made to household heat generation and usage.

Similarly, the electrification of transport will be reliant on supporting the adoption of EV technology through the provision of an appropriate charging infrastructure. Whilst this infrastructure may range from single home chargers to privately managed larger installations

[54], fundamentally the advent of EV's will further contribute to load at the LV level as well potentially offer a new reserve of energy storage.

The rise of distributed generation imposes further changes to the magnitude and shape of existing load profiles. Areas with high levels of domestic photovoltaics (PV) may experience voltage rises during sunny periods of low demand due to an excess of generation [55]. Wind generation is stochastic in nature and therefore can be challenging to forecast, depending on the time horizon and availability of appropriate data [56]. Figure 2-1 illustrates example idealised probability bands for domestic load alongside idealised wind and PV generation [49].

Renewable generation and low-carbon load is not homogenous. Each of these technology types features their own characteristics and dependencies, drawing on a range of environmental and behavioural factors that ultimately imposes an influence on load conditions. Even within a load type, there exists significant potential for load variation and therefore network impact. Modern EV's represent a range of battery sizes; the best-selling Tesla Model 3 features a 75kWhr battery [57], whereas Toyota plans to release an ultra-compact 8kWhr model [58] to support last-mile mobility in the near future. This variation translates into different network impacts through variation in charge time, current and user behaviours. Furthermore, the adoption of LV-connected renewables will not be homogenous at the distribution level due to variations in levels of urbanisation, demographics and climatological factors – therefore there is a need to incorporate localised predictions into future planning decisions.

2.2.1 Distribution Network Uncertainty Stack

It therefore is known that renewable integration will have an impact on load profiles at LV levels; the difficulty then becomes appropriately quantifying the extent of this impact in order to support network decision making. The challenge is to develop decision support approaches that can systematically deal with uncertainty, incorporating technical as well as practical knowledge [52]. Figure 2-2 represents an uncertainty stack concept for distribution networks which has been developed as part of this research project. Here uncertainty is the contribution of multiple functional layers, with "uncertainty" increasing as we infer information further from the physical layer of the network itself. Whether we wish to make decisions for the present day or future network, these decisions will be inevitably by supported by information drawn from the network in the past or present day.

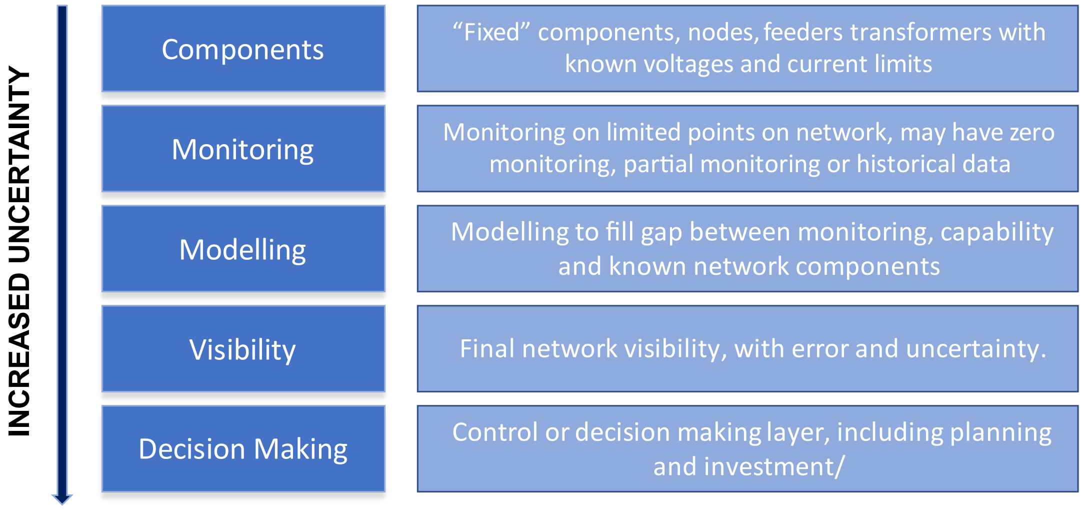


Figure 2-2 Generic uncertainty stack for distribution network studies

The component layer represents the physical network and associated assets; this could incorporate connected customer devices as well as DNO managed assets. It is this layer at which the truth occurs – whether a voltage exceeds a certain value on a feeder, or whether a tree falls on a line and causes an outage. However, whilst distribution networks are equipped with devices that can make autonomous decisions locally without human intervention (such as circuit breakers), there exist several layers of inference between the component layer of the network and the layer at which decision making occurs. The monitoring layer represents the sensor network and data collection infrastructure that is handled by the DNO; due to the need to balance sensor placement with capital costs this monitoring layer only offers a limited view of local network conditions at any one time [50]. The modelling layer exists to bridge the gap between the available data provided by the monitoring infrastructure and the inputs required by decision makers. This could be conditioning raw load data from the substation in order to project when load growth might necessitate reinforcement. This insight is represented as the visibility layer, where raw data has been combined with specialist knowledge and processing in order to infer a prediction about some part of the system. This prediction will incorporate some level of error or uncertainty, which must be considered as part of the final decision-making process, whether autonomous or human.

This illustrates that uncertainty in a distribution networks context is a composite of multiple interdependent factors spanning an entire cross-section of a DNO's responsibility, even when making simple predictions. The frameworks, paradigms, and goals of data collection and use have a significant impact on how data is gathered, analysed, managed, and understood [59]. Therefore when attempting to manage uncertainty in a decision making context it is necessary to develop tools that are sensitive to these influences.

Whilst challenging, the greater uncertainty prevalent on future networks also creates opportunity. Where previously static conditions were the norm, greater network uncertainty creates opportunities for new applications, services, and markets to fill the gaps in current capabilities.

2.2.2 Data Driven Solutions for Distribution Networks

The growth of data has been exponential in recent years, with growth of data continuing to exceed forecast expectations year on year. For instance, between 2002 and 2009 data traffic grew 56-fold globally, compared to computing power which only showed a 16-fold increase [60]. In turn, this massive growth of data compared to the growth of processing power has driven the uptake of a wide range of data analytic and data-driven machine learning techniques which now permeate a wide range of commercial sectors, from healthcare transport to social media and the internet of things.

The term data analytics encompasses a very broad definition but can generally be understood to mean the process of analysing raw data in order to draw useful insights. For modern data analytics, the expectation is that there is some level of automation or algorithmic conditioning involved to process the data into a format that will be ultimately interpreted by a human user [61]. Machine learning techniques fall under this term, and more specifically include models that can make predictions independent of the dataset they have been trained on. In both cases the benefit is the ability to rapidly reduce the time required to make decisions, if not entirely automate the process, or to draw insights from extremely large datasets that would be otherwise uninterpretable by human users. In order to support use of data analytics in a commercial environment, there must be appropriate IT infrastructure in place to support data collection, management and storage [62].

In contrast to growth elsewhere, the energy sector, and specifically distribution network operators, have not been so quick to adopt data-driven techniques into their commercial processes. In the post-privatisation period from 1990, until Ofgem introduced new mechanisms to incentivise innovation in the 2005 - 2010 price controls [63], DNO research & development spend had steadily declined to less than 0.1% of revenue [64].

This lack of investment has been driven by a number of factors. At transmission level, assets are traditionally high-value with a corresponding advanced level of communication and control capabilities. In contrast the historically passive function of distribution networks combined with the typically low value of assets has resulted in a modern-day system which offers limited or often zero data collection capability. For many power system sensors, including many emerging and state-of-the-art devices, the majority of data is either not logged, or is quickly overwritten [7], inhibiting the potential for data analysis.

Even when data collection is present for LV network assets, data sources can be fragmented with poor quality of data [65], further degrading the insights offered by already limited datasets. Furthermore, with limited profit margins, it can be difficult for distribution network operators to undertake technology upgrades and new analysis techniques when the returns are uncertain. Additionally, even the associated costs of gathering, storing, and analysing data can represent significant investment [66], necessitating a strong commercial justification prior to investment in novel data analytics techniques.

Despite the existing barriers to deployment of data analytic techniques for distribution networks, there remains significant interest in the potential value that can be offered through novel data-driven methods. The additional load posed by the electrification of heat and transport as well as the wider uncertainty contributed by distributed generation is driving DNO's to seek alternative solutions to physical network reinforcement, which can be costly as well as disruptive to customers. The high number of low-value assets managed by DNO's poses a further difficulty due to the decision-making overheads involved. The influence of renewable integration has an impact across every function of a DNO's portfolio; from real time operational tasks to planning decisions over a twenty-year period. At present there is a correspondingly wide range of data-driven techniques developed for distribution network applications through research as well as innovation projects. Key areas include [67]:

Technique	**Applications**
Load forecasting from input data	• Prediction of future energy demand for infrastructure planning [68]
Fault detection	• Reducing downtime through predictive maintenance [69]
Information extraction from existing load data	• Analysing consumption patterns for customer segmentation [70]
Condition monitoring	• Monitoring transformer health to extend lifespan [71]

Table 2-1 Data-driven techniques and applications for distribution networks

Regardless of the final application, the challenge becomes to appropriately integrate data analytics techniques in a way is complementary to future power system growth. Data analytic techniques will not be the solution for all issues faced by network operators and needs to be considered alongside the constraints of the power system and commercial environment. The relationship between potential applications, monitoring infrastructure, data processing and data visualisation must be considered if data analytic techniques are to be fully exploited in a distribution network context [67].

2.3 Existing Work

Renewables integration in the UK has been an increasingly important topic for both academia and industry since the commitment to emissions reduction made by the Climate Change Act 2008 [18]. In 2023, the UK government expected it's goal to decarbonise the UK power system by 2050 to require £275-375 billion of public and private investment, alongside £50-150 billion of investment from electricity network operators [72]. Since then there have been a range of approaches developed in order to predict and manage future network load conditions as a product of greater renewable penetration, new markets and services as well as changing consumer behaviour.

2.3.1 Trial Data and Industry Studies

To date, the analysis of potential impact to LV networks contributed by new renewable load types has been supported through a variety of Ofgem supported innovation projects which has resulted in a pool of disaggregated renewable load data to draw on. Concluding in 2015, the UK Power Networks (UKPN) led Low Carbon London trials recruited customers for EV and heat pump trials in order to collect data and gain insights on possible future load profile impacts [73]. The heat pump component of these trials were fairly small scale, representing 19 households fitted with a mix of air and ground source heat pumps in the UKPN licence area.

In a similar vein, the My Electric Avenue project recruited clusters of households to trial EV's over an 18-month period in order to gain insight into realistic EV usage patterns [74] . In both cases the aim was to collect disaggregated load data in order to support predictions of future potential load conditions for increased renewable penetration. Other works have focused on examining aggregated substation load data in order to provide predictions of future low-carbon profiles. The LV Network Templates project developed an approach for predicting load at unmonitored substation, on the basis of developing template load profiles derived from monitored assets [75].

More recently, the larger scale Renewable Heat Premium Payment (RHPP) scheme collected electrical heat load data from 700 sites with 2-minute heat and electricity data collected from 31st October to 31st March 2015 [8]. This offered a significantly larger sample size of domestic heat pumps (HPs) combined with increased temporal resolution of data, which provided the source data for the GB-scale analysis of increased electrical heat pump penetration performed in [76]. However, due to the anonymisation of individual households and lack of supporting metadata, it is not possible to directly infer a relationship between electrical heat load and geospatially linked parameters. Therefore, whilst the RHPP trial data is suitable for modelling large populations of heat pumps, it is not directly suitable for the very low populations and low levels of aggregation found typically found at LV level.

At present the UK government-led Electrification of Heat Demonstration project is also underway, which will monitor 750 homes fitted with electric heat pumps over the project duration [77]. A key objective is to capture electrical heat load for a comprehensively representative range of UK building types beyond what has been captured in previous trials.

More recent innovation projects have seen distribution network operators' trend towards more sophisticated techniques.

2.3.2 Predictive Models

Alongside industry studies, there has been extensive development of predictive models that model possible network impacts given a certain level of renewables penetration, taking some consideration of LV-level specific issues. In order to accommodate the uncertainty associated with predictions, probabilistic approaches have been popular. [78] probabilistically models potential heat pump impact on low voltage networks using limited combined heat and power (CHP) data as a stand in for electric heat pump (EHP) data, quantifying expected network impacts with a defined standard deviation. The usefulness of this approach is constrained by the relatively narrow dataset used for training the model. Similar approaches have been developed for other renewable load types; [79] quantifies the impact of EV's on LV networks using a Monte-Carlo approach. EV load profiles are drawn from My Electric Avenue [80]; whilst this consists of 18 months of high-quality EV load data for over 100 customers, the relatively small sample size and constraints when recruiting customers create the potential for demographic bias in this approach.

Despite the high data requirements necessitated by the probabilistic approach, any real-world study will be composed of probabilistic as well as deterministic elements. Therefore, there remains the question how to incorporate these techniques effectively in a real world decision making environment. For models developed using trial data, there is the difficulty of ensuring that the training data remains applicable for the target population under study. For LV networks where there may be a low diversity of customer load profiles, these effects cannot be neglected. Even within the relatively small geographic area of the UK, there exists a wide range of demographic, socioeconomic and climatological variation amongst households. As has been illustrated by the examination of smart meter data coupled with ACRON demographic information [81], demographic influences can play a role in determining load magnitudes. The uptake of domestic PV in the UK demonstrates [82] the strong localisation of uptake, rather than latitude being the primary factor in number of installations. Physics based models, whilst less common, are also subject to this concern. Whilst a physical model can capture a system in great detail, when designing a system where load is dependent on human behaviour, there is a need to draw on external sources in order to determine how these behavioural factors will influence load.

Whilst difficult to quantify, the expectation that the utilisation of data analytic and machine learning methods in industry is low compared to the wealth of techniques available in the body of research. There exist several barriers to adoption; some of these barriers will be institutional, posed by the historic low investment in energy innovation, particularly for DNO's [83]. Machine learning models have been highlighted as opaque, non-intuitive and difficult for people to understand [84]. Therefore, there exists an opportunity to develop probabilistic methods for supporting LV network decision making, where the contributions of uncertainty are treated in a systematic way, if not quantified.

2.4 Heat Pumps as a Decarbonisation Pathway

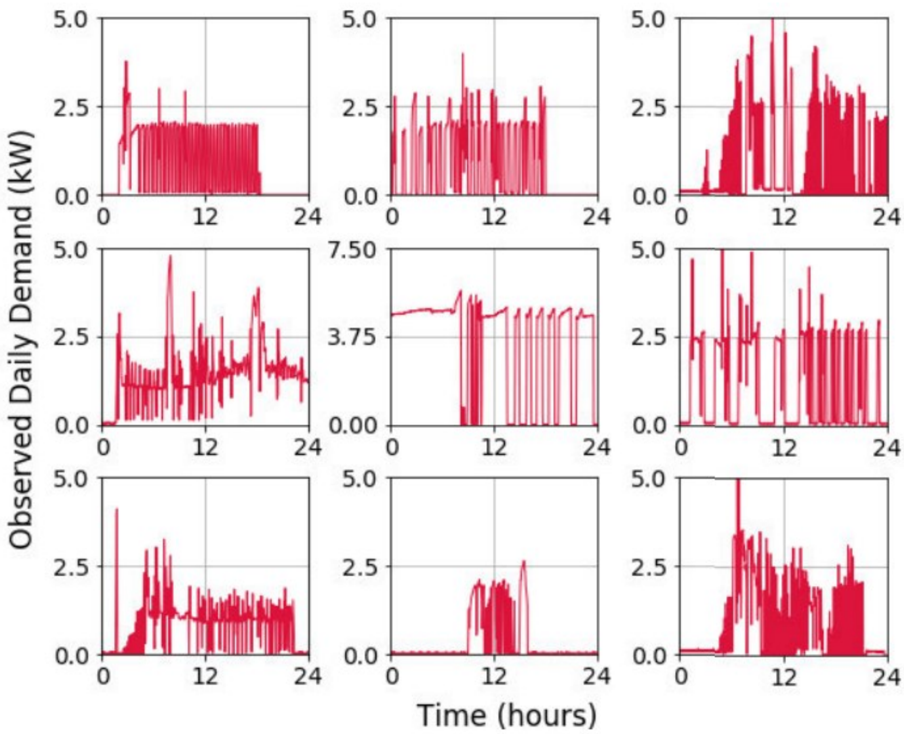


Figure 2-3 Intra-day heat pump electrical demand for nine sample customers on same winter weekday from Renewable Heat Premium Payment (RHPP) dataset.

Heat accounts for over one-third of the UK's greenhouse gas emissions [27], and the decarbonisation of domestic heating forms a key part of UK government strategy for reducing carbon emissions to target levels. To support this, the Sixth Carbon Budget delivered by the Climate Change Committee (CCC) in December 2020 has recommended the installation of over one million heat pumps annually by 2030 in order to meet decarbonisation goals [37]. From a power systems perspective, the additional low-voltage (LV) network loads imposed by rapid heat pump uptake will need to be accommodated by distribution network operators without breaching existing network limits or quality of service. Conversely, the introduction of significant electrified heat resource presents opportunities to support network flexibility or new distribution network-based services.

Reducing the contribution of heat to the UK's greenhouse gas emissions presents one of the largest challenges in achieving long-term emissions targets set by government policy. The contribution of domestic heating is estimated to average a third of household emissions [85]. In order to achieve 2050 Net Zero goals this must be reduced by a further 95% from 2017 levels [85]. Decarbonisation of the UK's heating sector will require a radical shift in the current status quo, expected to necessitate widespread adoption of low carbon heating with improved efficiency measures. Electric Heat Pumps (EHP) offer one potential low carbon alternative, reducing CO2 emissions of up to 25% per unit of heat generated [86]. In combination with a fully renewable electricity source, this can reduce the effective household heating CO2 emissions to zero. Advantages include acting as a low-regret option for off-gas grid households [30], and as a low-cost option for newer well-insulated builds. The growth of heat pump technology has been supported by UK government policy [87] and industry trials [8] but despite this, overall deployment remains low – 72,000 new domestic heat pumps were installed in the UK by the end of 2022 [88]. In contrast, the UK advisory body the Committee for

Climate Change (CCC) has recommended the installation of one million heat pumps annually by 2030 in order to meet decarbonisation targets [30]. This level of growth presents a major challenge for distribution network operators as heat pump loads at maximum output are significant both in terms of energy and power compared to existing domestic Low Voltage (LV) network loads.

2.5 Electrification of Heat for Distribution Networks

Distribution network infrastructure provides the "last-mile" of electricity supply to utility customers. Historically, this role has been a passive one. LV network assets would be sized using simple metrics such as ADMD [89], with low risk of the initial design constraints ever being exceeded due to the relatively static and predictable nature of LV-connected load over time. Power flows could be assumed to be unidirectional with no requirement to design for reverse power flow conditions.

The electrification of heat therefore imposes several immediate challenges for LV network operation and planning tasks. There is the fundamental difficulty of accommodating additional load on existing network infrastructure. Heat pump load is significant both in terms of energy and power compared to conventional domestic loads; peak load of a single heat pump is similar to existing peak domestic load [8]. Similarly, the energy consumption of a heat pump on a cold winter's day is on the same order of domestic energy consumption as charging an EV [2]. Furthermore, heat pump electrical load magnitude and shape characteristics are seasonal due to the positive correlation with domestic heating demand [76].

Whilst distribution networks are typically composed of primarily passive low value assets, the high volume of assets combined with the high heterogeneity of distribution networks across a given licence area presents further challenges for network operators. This variation can manifest in network topology, as well as customer demographics, local weather conditions and levels of urbanisation – all of which can influence direct electrical load as well as the long-term uptake of new load and generation sources on a feeder. As an example, the growth of domestic solar PV in the UK has been highly localised, as opposed to purely distributed with respect to geographic solar yields [90]. Therefore, there is a need to incorporate the local physical and demographic context when modelling heat pump electrical load for distribution network impact assessment.

2.5.1 Heat Pump Technology for Domestic Heating

Heat pumps offer a relatively new form of domestic heating for UK households, but the technology has been in use for decades prior to the recent resurgence of interest driven by decarbonisation strategy. An early concept for the technology was proposed by Lord Kelvin in 1854 [91], but this did not feature the closed cycle that is characteristic of modern systems. In the UK, the first major installation may have been a system that heated a group of buildings in Norwich [92]. This system achieved a coefficient of performance (COP) of 3.45 averaged over two winter heating seasons.

The oil crises of the 1970s triggered increased interest in EHP technology as an alternative means of heating buildings versus contemporary methods which were reliant on fossil fuels. In 1974 Denmark’s Ministry of Trade initiated an energy research programme to explore the feasibility of the technology as an alternative form of building heating [93]. By 1985, as much as 15% of Sweden’s housing stock was heated via heat pumps, increasing from basically 0% in 1980 [94]. Across Europe, similar developments were occurring in Germany [95] and Norway [96].

Today, heat pumps are part of a global market. In Europe, the top four countries with the highest proportion of household heat pump penetration are Norway (60%), Sweden (45%), Finland (41%) and Estonia (34%) [97]. In contrast, there were only 72,000 installations in the UK as of 2022 [98]. With an estimated 28.2 million households in the UK [99], these installations represent less than < 0.5% of UK households. The technology therefore forms a established part of the domestic heating sector for many European nations and further afield, but within the UK heat pump type systems do not have the same maturity as elsewhere.

2.5.1.1 Basic Principles of Operation

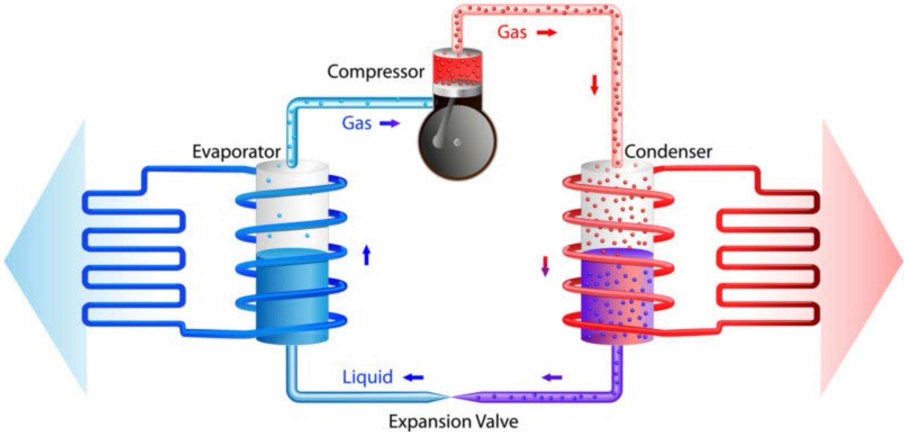


Figure 2-4 Basic principles of heat pump operation, reproduced from [100]

The underlying principle of a heat pump's operation is the reverse of a heat engine: mechanical work is used to move heat against its natural gradient from a cold location to a hotter one. For instance, from the outdoors into a home. A refrigerant such as CO2, or hydrofluorocarbon, is used to transport this heat, exploiting the physical properties of evaporation and condensation [101]. Through these principles, a heat pump is able to provide more heat per unit of electricity consumed. A typical COP of 3.0 would produce three units of heat of electricity consumed [102]. In contrast, a gas boiler might only product 0.85 units of heat for every unit of gas consumed [103].

2.5.1.2 Air Source and Ground Source Heat Pumps

Heat pumps can be divided into two main categories depending on the placement of the outside heat exchanger, either drawing heat from the air or from below ground [101].

Air source heat pumps (ASHP) extract energy from the air external to a household. Air/water systems use a hydronic system to distribute heat via wall radiators or underfloor pipes. Air/air heat pumps distribute the heat energy through a building via ducts [104]. This form-factor can be suitable for high-density housing where the installation of ground source heat pumps would be impractical [105]. However, the exposed location of the outdoor unit can result in performance reduction during particularly cold events.

Ground source heat pumps (GSHP) exploits the energy naturally stored in the ground as a heat source. This form-factor costs more to install than an ASHP type system [106], with a typical cost for an ASHP system estimated at £14,000 and cost for a GSHP at £28,000. The GSHP type form-factor is additionally more demanding of space due to the requirement to install the exchanger within trenches. However, despite the trade-off in cost and space, a GSHP system has a key advantage over ASHP system – improved COP at cold extremes. This is due to the fact that ground temperature is persistently higher than external air temperature during winter conditions.

Within the context of this work, the developed methodologies are not specifically ASHP or GSHP dependent. Where COPs have been selected in further sections, they have been selected to be representative of ASHP-type systems. However, with appropriate selection of COP, the model outputs can be tailored to be representative of ASHP or GSHP systems.

2.6 Existing Heat Pump Demand Modelling Approaches

The primary challenge when evaluating the impact of heat pumps on a distribution network is accurately quantifying the magnitude of additional electrical load contributed by the connection of heat pumps. The current low uptake of heat pump technology in the UK results in a general lack of operational demand data that could be used to facilitate heat pump effects analysis and general evaluation of network impacts. Excessive additional load will result in a significant impact on voltage and reduction in thermal headroom on a network, potentially resulting in a breach of operational limits. The difficulty surrounding heat pumps is that while their heat output is broadly proportional to outdoor air temperature on a seasonal time frame, at a daily and hourly level the demand profile for a single customer is determined by a broader range of factors.

The electrical demand required to meet a target heating demand for a household is influenced by several parameters including building type, heat pump type and building efficiency as well as the behavioural patterns of the individual household. In extreme cases, a small, poorly insulated building may require more input electrical energy to reach a heating setpoint than a large, very well insulated property. This heating demand primarily consists of the seasonally dependent component that is dependent on external air temperature, but heat demand for a household can also include demand for hot water. The methodologies developed in this work will primarily be focused on modelling the relationship between external temperature and the electrical demand required to fulfil a space heating requirement, but a base level of demand will be allocated to hot water consumption.

Therefore, for a single point in time, the additional electrical load presented to a distribution network due to heat pumps is a function of parameters specific to each household in addition to the common local outdoor air temperature conditions and time of day. This contrasts significantly with conventional domestic loads on distribution networks which are highly static and predictable in nature. The instantaneous electrical demand of a typically sized domestic heat pump can be equivalent or in excess of current daily domestic demand peaks [107]. In terms of energy, the average heat pump electricity consumption of 8kWh per day [108] is roughly equivalent to the existing average electricity consumption for a UK household of 8.5kWh per day [109]. Each additional heat pump connected to an LV network is roughly equivalent to the connection of an extra household and therefore is a serious consideration for network headroom at higher levels of penetration. Analysis and prediction of heat pump electrical demand modelling within the UK is currently constrained in the literature primarily to either small-scale physical models which require a high-level of specific system knowledge to make predictions [110], or methods which rescale existing heat pump trial data to achieve a deterministic outcome [76]. There are currently three fundamental approaches for modelling heat pump load profiles that have been used in the literature:

• Physical model that captures a detailed heat pump/ heating system but with limited capture of time of use effects across a population [110] [111]

• Use of existing gas or heating demand data, making assumptions about building type, building insulation and population information, [112], [113]

• Use of electric heat pump trial data; examine and rescale for time periods of interest [108], [76], [78]

These approaches all feature their own specific advantages and disadvantages depending on the specific area of study.

Existing physical approaches are well-suited for simulating highly defined models that clearly characterise one heating system; this makes them ideal for modelling highly specific behaviours such as fast start-up transients. Underwood et al. [110] developed a compressor-based parametric model for capturing seasonal performance of different manufacturer's heat pumps, which was able to achieve good results when comparing actual and modelled heat output. Other works further incorporate building parameters across a population when considering heat pump demand [111], but the approach lacks real demand data to support the full validation of results and it is therefore not possible to quantify the associated error. Heat pump electrical load and therefore its immediate impact on an electrical network is a function of several parameters that will vary from household to household; these include relatively fixed characteristics such heat pump type, building and insulation characteristics but are also strongly linked to ambient temperature conditions and behavioural routines which will vary seasonally. Furthermore, it can be expected there will be diversity in heat pump type, building characteristics and behavioural routines even within a local neighbourhood [114]. Figure 3-2 illustrates sample daily load profiles for nine different households on the same winter's day from the Renewable Heat Premium Payment (RHPP) dataset [115]. All households are based in England and therefore are exposed to similar daily temperature profiles and magnitude. Each customer load profile clearly features a distinctive shape and there is limited commonality from customer to customer. This combination of physical, seasonal and behavioural characteristics makes it very challenging to develop a fully representative physical heat pump model that can translate these population-variable parameters into an aggregated load profile that accurately reflects the energy, power and time of use characteristics of a real heat pump load.

For DNO's, both the power and time of use characteristics of electrical heat load are areas of concern for optimising network investment and operation. Simplistically, network assets must be sufficiently rated to ensure that thermal and voltage limits are not exceeded during periods of maximum load; for instance, during a cold winters day when electrical heat load would be at its highest. ADMD is a well-established network planning tool for sizing assets, which makes estimations on the peak power contributed by individual customers and then incorporates the effects of diversity to produce a diversity-sensitive overall peak load for a group of customers [116]. However, for load types such as heat pumps, electrical heat load is strongly linked to building occupancy and occupant routine, with periods of maximum demand centred around morning and evening peaks. Therefore, the time-of-use for electrical heat load is of interest for network capacity planning, as this will dictate whether additional electrical heat load will exacerbate existing electrical peak load and potential negative or beneficial interactions with other load types such as solar and electric vehicles. Finally, whilst daily energy demand does not have the same direct relationship to determining required asset ratings as peak power, it offers several useful insights. The expected electrical energy consumption per day can support capacity planning activities and optimisation of asset utilisation, either through planning or demand side management activities. As the load-mix connected to households becomes increasingly complex – potentially including electric vehicles, solar generation, heat pumps as well as novel tariff structures – it becomes more important than ever for DNO's to assess potential adverse interactions between these new load-types as well as identify opportunities for more efficient utilisation of existing assets and infrastructure.

A more straightforward approach to modelling heat pump demand is to take existing gas or heating demand data and rescale this the equivalent electric heat pump demand based on an appropriate Coefficient of Performance (COP) figure. This method has been applied for showing large scale effects for the transition to greater levels of heat electrification in the UK [112], whereas elsewhere electrical demand profiles have been derived from ambient temperature and heating demand profiles with an hourly resolution [113]. Whilst strongly linked to the true heating demand characteristics, this method has limitations when applied to LV networks on daily or hourly resolutions. Current gas demand magnitude is partially shaped by equipment type (i.e. combi versus condensing boiler) as well as home characteristics and behaviour. Alteration of the heating system will reshape heating demand according to EHP characteristics. This may potentially also alter pre-existing behavioural thermal routines, such as when occupants choose to enable household heating [114]. Due to lower flow temperatures than conventional boiler-based systems the time of use characteristics of heat pumps can be anticipated to be different compared to existing profiles and will potentially be spread more widely across the day. In contrast to physical models and heating demand-based approaches, methods that utilise existing EHP demand data from trials are able to mitigate the requirement to fully characterise the heating system in order to define the electric demand. The primary restriction with this approach is that due to the limited number of heat pumps active within the UK there is sparse operational data from which to draw conclusions about heat pump network impact. Consequently, the level of detailed heat pump analysis involving large populations is limited and generally features linear rescaling or averaging of the aggregated profiles in order to assess heat pump demand magnitude for a given time window.

Models based on real heat pump demand data have been developed in the literature, circumventing the need to fully characterise a physical heating system. A high-resolution probabilistic model drawing on operational data from 72 micro-CHP (combined heat and power) units during field trials in 2011 was developed for electrical heat pump demand prediction [78]. The probabilistic approach of this study enabled the definition of a range of possible demand values with respect to heat pump penetration. However, this study is reliant on the fact that micro-CHP technology represents a good approximation of EHP demand patterns and does not draw on real EHP operational data. Recent UK trials have greatly improved the availability of domestic demand EHP data [115], [2], however limited analysis has been performed to date. At present the majority of heat pump demand modelling studies only focus on averaged profiles at operational extremes. As the kinds of loads connected to LV networks become more diverse, with a mix of PV, EV, wind and low carbon heating technologies, there is a strong need for the capability to model realistic heat pump demand profiles alongside the interactions of other technologies. The methodology described in this paper will define a composite approach between a fully physical demand model that requires detailed inputs and can be difficult to validate, and data-dependent approaches that primarily rescale existing demand data. The concept of synthetically generating demand profiles from real data has been used in other domains as a way of facilitating system analysis for applications where real data may be sparse or difficult to obtain [2], [117]. At present there has so far been limited use of these techniques for heat pump demand applications. Synthetically generated demand profiles derived from real operational data present an opportunity to develop a model that characterises the difficult to capture elements of a physically defined heat pump model that can be validated against operational data. This maximises the value that can be drawn from limited real-world data that is typically costly and practically difficult to obtain.

2.6.1 Modelling Electrical Heat Load at Geographical and Temporal Scales Suitable for LV Network Impact Assessment

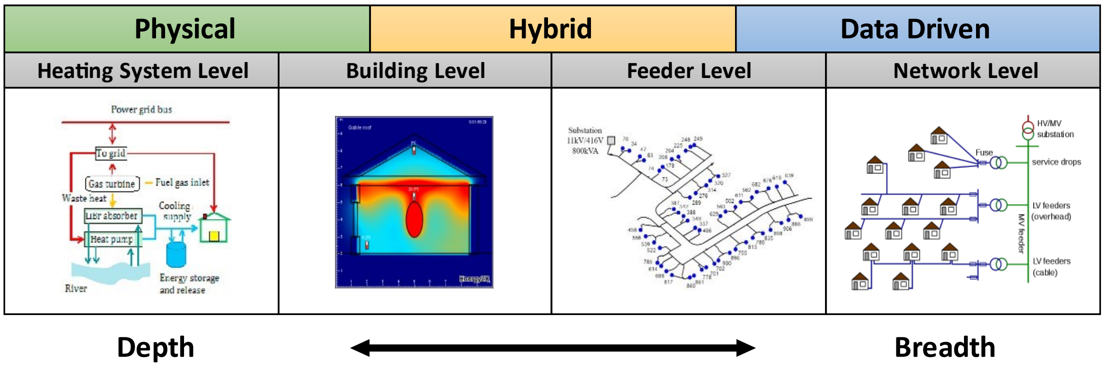


Figure 2-5- Common heat pump modelling approaches versus relevance to scale of approach.

Assessment of additional electrical heat pump penetration at the distribution network level is concerned with quantifying heat pump electrical load shapes and magnitudes, such that their effects on existing asset voltage and current limits versus increasing penetration can be assessed for network operators. However, this modelling context represents a middle ground compared to established heat pump electrical load modelling techniques and this necessitates the development of a modelling approach that is sensitive to these constraints.

Presently there are two main established branches of heat pump electrical load modelling; the highly detailed physical approach that features high individual system detail, and the data-driven approach which draws on real-world data but is often unsupported by sufficient underlying information to explain why and how the real-world electrical heat load manifests as it does. The basic premise of both approaches will be outlined and contrasted to the specific requirements of LV network load modelling in this context.

2.6.1.1 Established Heat Pump Electrical Load Modelling Approaches

Physics based models are ideal for small-scale for individual household studies, where the heating system is highly parameterised and well-defined by the model designer. The physical parameters may be representative of a 'real-world' system or drawn from manufacturers datasheets or inferred otherwise from available datasets. The primary observation to be made here for this modelling approach is that the output of the model can be directly related and understood to be a function of the model inputs and structure. This approach is well suited for modelling transient electrical effects with degrees of high fidelity. However, whilst the relationship between model inputs and outputs is clear, the transferability of the model inputs and model assumptions on a wider scale is less secure. For instance, the physical building characteristics may be defined in great detail for a physics-based model. However, how well the selected building characteristics represent larger populations of interest is unknown. Therefore, physics-based approaches need to be supported with quality supplementary data in order to be usable at scales beyond the individual household level.

In contrast, data-driven approaches bypass the need for detailed parameterisation of physical systems by drawing on load data recorded from households fitted with heat pumps. This kind of approach is well suited for making observations about potential heat pump electrical load effects at scale, as individual effects can be averaged out due to the aggregation of load shapes for high numbers of customers [3]. However, due to the existing legal obligation for anonymisation of data, often there is poor or limited metadata associated with individual customer load profiles. This makes it very challenging to correlate load shapes and magnitudes observed to specific model inputs such as housing type, size or local climate conditions. Therefore, whilst results are broadly indicative for customer groups of hundreds upwards, there remains the difficulty of translating the trial data from the original sample set to new target areas of interest for low customer numbers.

For both physics based and data-driven approaches, the primary difficulty is in the ability to translate the outputs of these models to areas outside of the original model. This becomes key when dealing with distribution network analysis [118].

2.6.1.2 Heat Pump Electrical Load Modelling Requirements for Distribution Networks

In the UK, there are approximately 230,000 LV substations and 350,000 pole mounted LV transformers, with each transformer on average servicing 120 customers or less in an urban setting [119]. This represents over half a million discrete geographic areas of interest for consideration, with each area representing a unique grouping of building, demographic and climatological characteristics as well as network topology that ultimately determine electrical heat demand with respect to local temperature conditions.

Administrative Region	*Median Number of Households*	*Number in United Kingdom*
Household	1	28,200,000
Unit	14	1,790,000
Sector	3,035	12,463
District	10,244	3,118
Area	215,165	124

INCREASING AGGREGATION

Table 2-2 Median number of households per postcode geographic code-type versus number of unique code-types within UK

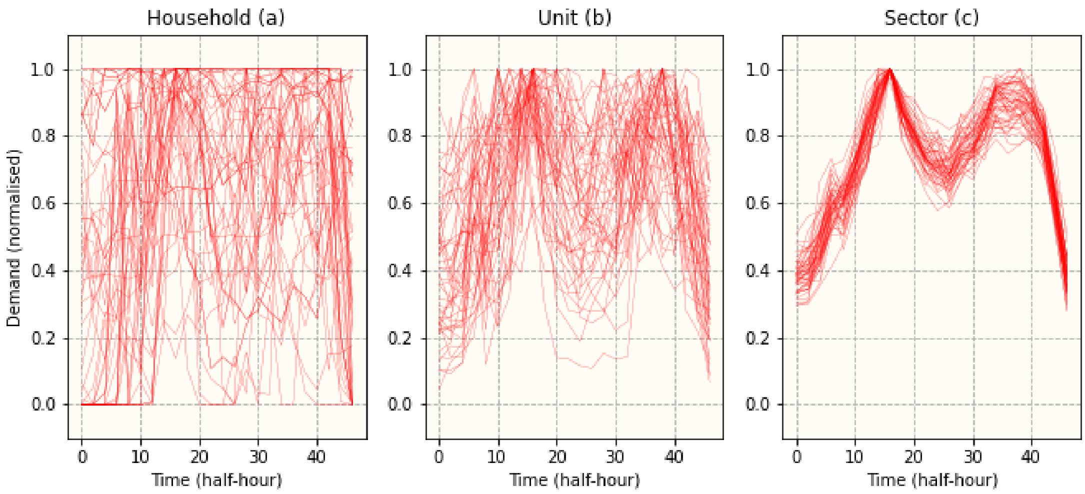


Figure 2-6 Normalised Shape Aggregation Effects on Total Load; Total Electrical Heat Load for Household (a), Unit (b) and Sector (c)-scale administrative regions

Table 2-2 outlines administrative regions of the UK with respect to median number of households [120] and the number of unique postcode geographic code-types versus increasing area scale [121]. For distribution network studies concerned with conditions on a specific LV feeder or network, the geographic scale and number of households is typically from the sector-scale downwards. Figure 2-6 demonstrates the effect of aggregation on the total load imposed through a network node using a randomised set of customers from the RHPP dataset with respect to these geographic scales. For very low levels of aggregation in the Household to Unit-scale, as defined in Table 2-2, the magnitude and shape characteristics are highly specific to the localised physical and behavioural parameters of the specific households. For high levels of aggregation, such as at the Sector level, the effects of localised magnitude and shape characteristics are lost and converge on the same average solution. Therefore, for low levels of customer aggregation, load modelling must consider how to incorporate the locally specific shape and magnitude characteristics that are otherwise averaged out for high customer numbers.

To summarise, an electrical heat model for LV network impact assessment aiming to incorporate the effects of localisation must be able to incorporate:

- Geospatial heterogeneity; the specific physical and behavioural context of the distribution network segment under analysis, versus the average context for the entire DNO licence area. Physical factors incorporate building construction, age and type as well as local climate. Behavioural context includes householder demographics and thermal routines.
- Geospatial granularity/low levels of customer aggregation; the ability to incorporate the effects of local model inputs down to the low hundreds of households or less.
- Temporal granularity; capturing the effects of electrical heat load at a temporal scale relevant for LV networks analysis; typically hourly or half-hourly for broad network impact assessment.

2.6.2 *Heat Demand Load Components*

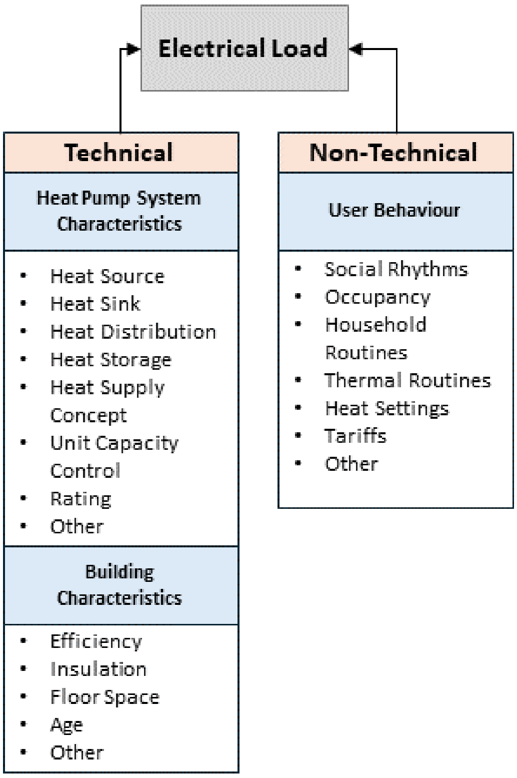


Figure 2-7- Components that contribute to the electrical load imposed on the network by a heat pump (not exhaustive).

The geospatially variable factors that contribute to direct heat demand, and therefore heat pump electrical load can be defined in two categories:

- Physical, or technical components; the parameters that define the heat pump and building characteristics.
- Behavioural, or non-technical components; thermal routines and comfort levels of the occupants which are primarily behaviourally driven.

The energy required to heat an individual household to a target level can be expressed generically as shown in (1) using the standard specific heat capacity equation [122] , where ΔT

represents the difference in external versus internal temperature, C represents the specific heat capacity of the overall household J/(kg•°C), m represents the mass of the overall household in kilograms (kg) and Q represents the input energy required to achieve the target temperature change in joules (J).

$$Q = mC\Delta T \tag{1}$$

$$Q = \delta mC\Delta T \tag{2}$$

This expression can be further modified to include the behavioural component. A duty cycle factor, δ, is added to (1) in order to create the relationship expressed by (2) This factor ranges between 0 and 1 and represents the proportion of time the heating system is in the on-state during a time period; a δ of 1 is equivalent to heating being constantly on whereas a δ of 0 represents heating being continually in the off-state. In practice, this factor will be somewhere between these two extremes. By varying the behavioural δ component, and the physical components mC and ΔT the impact on Q can be considered. mC encompasses the aggregate effect of a building's construction, size, insulation and physical parameters whereas δ reflects the aggregate effect of a residents age, economic status and personal preferences that otherwise modulate the behaviour of the heating system.

This equation (2) however, is based on several simplifications and reliant on several assumptions. A uniform specific heat capacity C is assumed for the entire household, when pragmatically a dwelling will consist of different structural materials, as well as furnishings, insulation, water and air. Similarly, as single value is assumed for m to represent the overall mass of the household, which assumes that all mass will be uniformly affected by a heating process. ΔT simplifies the relationship between external and internal temperature, assuming that temperatures are uniform both within and external to the household. In reality, there will be natural temperature gradients across a household due to shading, layout and construction. Finally, the duty cycle parameter δ incorporates the behavioural component of the heating system but does not account for any effects from thermal inertia and any non-linearities in transitioning between the two on-off states.

Therefore, these expressions do not incorporate time to reach target temperature or account for heating losses but demonstrate the basic relation between physical and behavioural components and their contribution to overall heat demand.

2.6.3 Limitations of Existing Datasets for Informing Physical and Behavioural Load Components

As has been described previously, electrical heat load can be expressed as the combination of the load shape and load magnitude. Both load shape and load magnitude functions will vary on the basis of geospatially variable parameters that contribute to electrical heat load, such as building type and construction.

The actual values of δ and mC that drive an individual's specific thermal comfort level, the equivalent heat demand and the necessary electrical energy to achieve this is difficult to quantify due to the behavioural elements as well as the granularity of the physical parameters required. This interplay necessitates an appropriate level of detail for model inputs which can be challenging to obtain.

For studies incorporating high numbers of customers, e.g. at a regional or national level, these effects can be neglected due to the effects of aggregation for high populations [76]. However, for LV-scale applications where the number of households and corresponding heat pump population is small their influence is of greater relevance.

Previous works have already identified a relationship between occupant demographics, building type and overall household energy use, where details about the occupants and building are inferable from smart meter data [123]. For EVs, demographic effects have been shown to result in different probability distributions for EV usage [124] which translates into demographically influenced changes in network load. Similarly, it has been demonstrated that household energy consumption patterns are sensitive to householder demographic and affluence [81] [125].

In practical terms, this may translate into higher electrical demands for groups of houses with poorer standards of insulation, or conversely more affluent households with larger interior volume. Like many domestic load types, heat pump usage is also behavioural; identically rated heat pump and building systems may impose radically different electrical loads due to the heat comfort preferences and routines of the individual resident [114].

Existing works [76] [126] have highlighted the dependency on limited samples of heat pump load data for constructing load models. This introduces the risk that modelled load profiles do not capture the local influence of building and behavioural parameters, and therefore do not capture the corresponding delta between heat load inferred from trial datasets versus heat load for the target area. Recent works have tried to address this problem by developing parameter based predictions on how heat demand can vary versus building type and size [111], whilst the variability of heat demand versus individual behaviour has also been documented [114]. Predictions are constrained by availability of locally appropriate data in the public domain and are reliant on oblique parameters that may not be recorded reliably for all properties.

Energy Performance Certificates (EPCs) capture property floorspace and nominal efficiency though are only published when a property is sold or rented [127]. Therefore, in many parts of the UK there are regions with partial or very low EPC coverage. Metadata such as number of rooms and occupants is captured in UK census data, but this can be insufficient to capture the inherent variability in residential property due to age, construction techniques as well as local demographic factors [128]. Furthermore, it is difficult to validate the output of these models with a specific value that can be directly correlated and validated versus demand.

Within the UK and worldwide, significant diversity exists across building types, behavioural profiles as well as commercial heat pump type and configuration [128]. The absence of sufficiently granular and comprehensive datasets capturing these parameters at appropriate resolutions for physical thermal models, combined with the potential diversity of these parameters, creates a need to develop alternative methodologies for robustly modelling locally granular heat demand at geospatial and temporal scales appropriate for LV network analysis.

2.7 Contributions of this Research in the Context of Prior Work

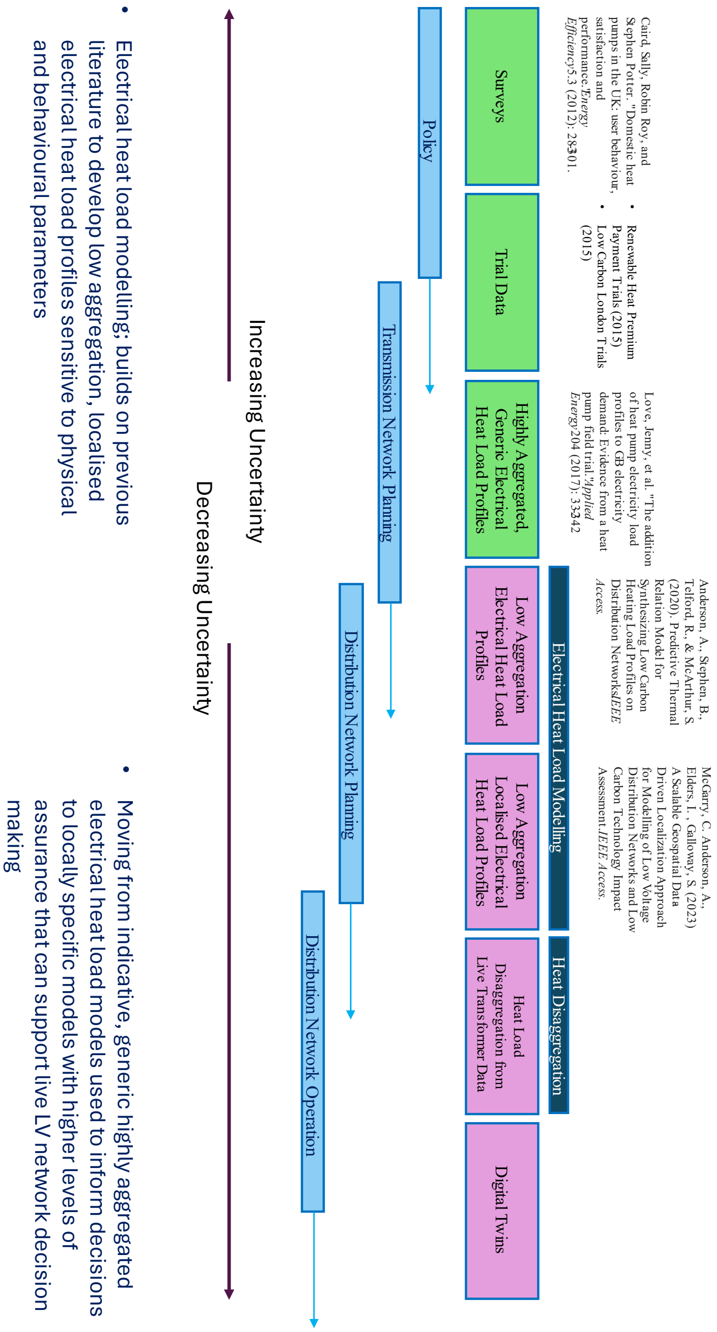


Figure 2-8 Contribution of this Research in the Context of Prior Work

This chapter has outlined the wider context of this work, with respect to the ongoing climate crisis and the concurrent efforts of international and national organisations to reduce and mitigate the effects of greenhouse gas emissions. Within the UK, significant focus is allocated to the decarbonisation of heat, and correspondingly, the electrification of domestic heating through the adoption of low-carbon heating solutions.

The rapid adoption of electrical heat pumps at the distribution network level presents a series of technical obstacles for network operators and asset owners for both planning and operational tasks. Against the wider backdrop of LV network LCT integration, the technical difficulties introduced by greater electrification of heat are in many ways common with the challenges faced by increased adoption of electric vehicles and LV-connected solar and wind generation. Unlike historical domestic load profiles which exhibit fairly static shape and magnitude characteristics, these new load types are sensitive to geospatially variable effects such as weather, demographics and building stock characteristics. The influence of these local factors has already been demonstrated to manifest in different voltage and current effects specific to the feeder under analysis. Given the scale of the entire distribution network, this represents over half a million specific sets of geospatially grouped parameters that can influence local electrical heat load. Therefore, whilst this work focuses on the specific problem of modelling electrical heat load appropriately at distribution network level, the higher concepts are universally applicable for modelling new load types at distribution network level.

The increased complexity of the energy-mix connected to LV feeders – stochastic solar PV generation, energy storage and additional electrical load contributed by EHP's and EV's – imposes additional pressure on DNO's to maintain quality of service and security of supply without incurring significant increases in expenditure. DNO's face transitioning from managing a passive network that requires minimal operational intervention, where primary functions can involve fault isolation and service restoration, online power flow and switch-order management [129]. Instead, the integration of LCT's creates new opportunities for a

DNO to take a more active role in network management as a distribution system operator, or DSO. DSO's functions can be broadly summarised as taking an active stance for several functions that were not previously required: local balancing of generation and load, facilitating uptake of LCT's within a licence area by simplification and expedition of connections processes as well as acting as a facilitator for new market structures amongst various energy stakeholders [130].

To date previous works have focused on examining electrical load profiles on a highly aggregated scale, suitable for national or regional analysis. These efforts have been naturally constrained by availability and quality of trial data. This work aims to build on previous electrical heat load modelling efforts, by developing electrical heat load profiles that are sensitive to local building and demographic parameters, in addition to weather conditions. Understanding short-term and longer-term impacts of electrical heat load within a licence area is key for DNO's seeking to optimise network utilisation.

In the short-term, existing electrical heat load on a feeder is predominantly sensitive to external air temperature; this temperature dependency therefore results in periods of very high or very low electrical heat load depending on the time of year. The ability to predict electrical heat load with confidence throughout the year enables DNO's to procure flexibility when required or encourage demand response participation when balancing electrical heat load usage with other load-types on a feeder. Over the longer term, the rate of uptake of EHP-type heating on feeders will evolve, generally resulting in increased electrical heat load across a licence area, with the potential for areas of concentrated EHP uptake to emerge. Ultimately, even in acting in a DSO-type role, future network operators will need to ensure that investment is suitably applied to reinforce the network appropriately for future load conditions.

The methodologies in this work offer additional capabilities to DNO's over both the short and long-term in terms of predicting electrical heat load with respect to localised external air temperature, for customer groups of low diversity, with additional heat demand localisation capabilities specific to existing gas demand usage in an area.

Furthermore, this work aims to step beyond the standalone modelling approach that is prevalent in the literature, towards methodologies that contribute to network decision making in a real environment. The reliance on pure trial data or isolated physical models inhibits the final usefulness of a model for real network applications; there is still a gap between modelled outputs and how a network operator or user should apply these findings for decision making in a network's context. However, there is still a need for these approaches in the absence of complete visibility at the LV level. Therefore, this work will demonstrate an integrated concept that aims to augment modelled electrical heat load with live data disaggregated from the LV transformer using a novel approach. This represents an effort to overcome the limitations of static models based on limited data or physical approaches, by supporting the models with inferred contextual information drawn from the specific network of interest.

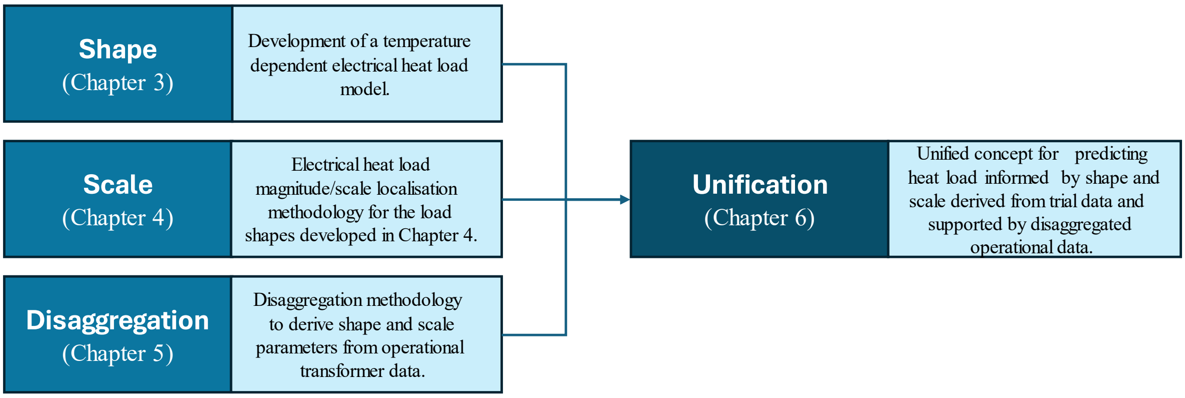


Figure 2-9 Research Overview

The high-level contributions of this work are illustrated in Figure 2-9. Chapter 3 will introduce a novel methodology for deriving electrical heat load shapes sensitive to external air temperature, and suitable for examining networks with low customer numbers and therefore low levels of diversity. This is in contrast to previous works which have focused on electrical heat load shapes at winter extremes, and averaged results for customer group sizes greater than those found on typical LV feeders.

Chapter 4 builds on the work in Chapter 3 by outlining a methodology for further localisation of the electrical heat load shapes derived from trial data. Chapter 4 introduces a method for scaling electrical heat load with respect to existing measured annual gas demand for a postcode, allowing for the prediction of electrical heat load not only with respect to local external air temperature, but geospatially variable factors such as building type, construction and household demographics.

Combined, Chapter 3 and Chapter 4 therefore offer a methodology for predicting the shape and scale of electrical heat load with respect to external air temperature, existing annual gas demand, and number of customers. This approach is fundamentally dependent on the parameters derived from static trial datasets, and Chapter 5 seeks to overcome these limitations by demonstrating an approach for informing shape and scale parameters from operational transformer data rather than static datasets.

Finally, Chapter 6 draws the methodologies together in a unified concept that seeks to use the scale and shape information encoded in static trial datasets, supported by the locally specific insights that can be derived from the aggregated load of a real world LV transformer.

Chapter 3

Predictive Thermal Relation Model for Synthesizing Low Carbon Heating Load Profiles on Distribution Networks

This chapter describes the limitations of existing electrical heat load modelling methodologies and presents a novel probabilistic electrical heat load model developed from trial datasets. This builds on previous works which have focused on modelling highly aggregated heat pump load at winter extremes rather than across the entire range of outdoor air temperature conditions. This methodology is sensitive to local outdoor air temperature as well as number of customers.

3.1 Summary

The introduction of electric heat pumps as a low carbon option for space heating offers a potential pathway for reducing the carbon emissions resulting from domestic heating demand in the UK. However, the additional power demands of heat pumps over conventional domestic loads have the potential to significantly erode network headroom, particularly at the distribution level. The uptake of this technology within the UK is currently limited and the effects of widespread adoption on distribution networks are not well characterized due to the sparse availability of operational heat pump demand data. This chapter outlines a methodology for quantifying the demand impact of heat pumps on Low Voltage networks sensitive to local outdoor air temperature by deriving fundamental thermal relationships from real heat pump electrical demand data. These relations can then be applied to predict demand for new studies independent of the geographic specifics of the original dataset. The strength of this model is in the ability to predict an aggregated hourly heat pump electrical demand profile that reflects local outdoor air temperature and intra-day usage as well as population size, thereby also accounting for diversity effects that are difficult to capture in physics-based models. This work augments the usability of limited existing data by facilitating demand analysis sensitive to local outdoor air temperature, rather than blanket rescaling of existing customer data as has been performed in previous studies. This creates future opportunities for examining heat pump demand sensitivity for different geographic locations against existing heat pump assessments, as well as performing studies which incorporate multiple low carbon technologies connected to a Low Voltage network.

3.2 The Challenge around Heat Pump Demand Modelling

The increase in network load contributed by heat pumps presents a serious threat to the existing thermal and voltage limits of LV network assets. In order to maintain quality of service for customers whilst minimising the need to incur costly network reinforcement, network operators require a clear view of how heat pumps will impact networks at a local level. For this purpose, predictive demand models that use operational demand data have an advantage over conventional physical demand models, in that they can capture individual household behavioural and diversity effects that are difficult to parameterize in physical models. However, there is currently very limited availability of UK-based operational heat pump data to draw on for examining heat pump network effects. Furthermore, heat pump demand is highly sensitive to local outdoor air temperature ; conditions can be highly divergent even within a limited geographical area due to factors such as local topography and level of urbanization. This necessitates a model that captures the full temperature to demand relationship rather than relying on operational maximums. Traditionally, load prediction at LV level has been limited to modelling peak annual demand and rating physical assets appropriately in order to ensure there is sufficient headroom to meet this modelled peak [131]. The need to decarbonize the energy sector necessitates the further uptake of LV-connected low carbon technologies such as heat pumps, alongside wind, PV and EVs. The inherent stochasticity of these load types with potential for new failure modes demands new prediction approaches beyond the historic method of modelling bulk aggregations. On this basis, the contribution of this chapter is a methodology for quantifying the impact of heat pump demand on LV networks sensitive to local weather conditions by deriving fundamental thermal relationships from real heat pump electrical demand data. These relations can then be applied to predict heat pump electrical demand for new studies independent of the original dataset, thereby maximising the utility of sparsely available heat pump demand data. The cost and complexity of capturing useful heat pump demand data at scale limits the availability of quality datasets for future EHP impact research; by offering a generalised model this work seeks to offer a transferable method that can be tailored for impact studies beyond the original dataset sample population.

This methodology extracts electrical demand versus hour of day and electrical demand versus outdoor air temperature relationships from individual customers in an operational dataset and translates these relationships into a format that can be then used to probabilistically predict heat pump demand through a black-box type approach. Linear scaling factors are derived from the operational dataset to act as a proxy for the variation in building type, heat pump type and system efficiency that would be seen in a typical UK population. By directly modelling these relationships versus electrical demand, the need to transform a heating demand into an electrical demand is circumvented. The majority of previous heat pump demand impact studies have focused on predicting demand for extreme cold temperatures rather than fully capturing the temperature/demand relationship [108], [76]. A key strength of this model is the ability to generate a heat pump demand profile that is sensitive to local outdoor air temperature conditions, hour of day and population size, thereby accounting for diversity effects as well as temperature. Furthermore, by incorporating the full electrical demand versus outdoor air temperature and time of day relationship, this model facilitates the study of heat pump demand impact alongside other low carbon technologies on an LV network for conditions other than extreme cold days. The mean error and standard deviation of this model are tested versus two heat pump demand datasets, with consistent results versus population size and outdoor air temperature for both cases. This indicates that the developed approach will be generally applicable for UK based heat pump populations, facilitating analysis of LV networks with demand profiles tailored to local weather conditions. In section 3.3 of this chapter, the selected methodology for modelling heat pump demand is described. Section 3.4 presents the validation results as well as primary model results. Section 3.5

discusses the results, section 3.6 outlines potential applications and a basic case study and 3.7 concludes the chapter with further possible work.

3.3 Probabilistic Prediction of Localised Heat Pump Demand

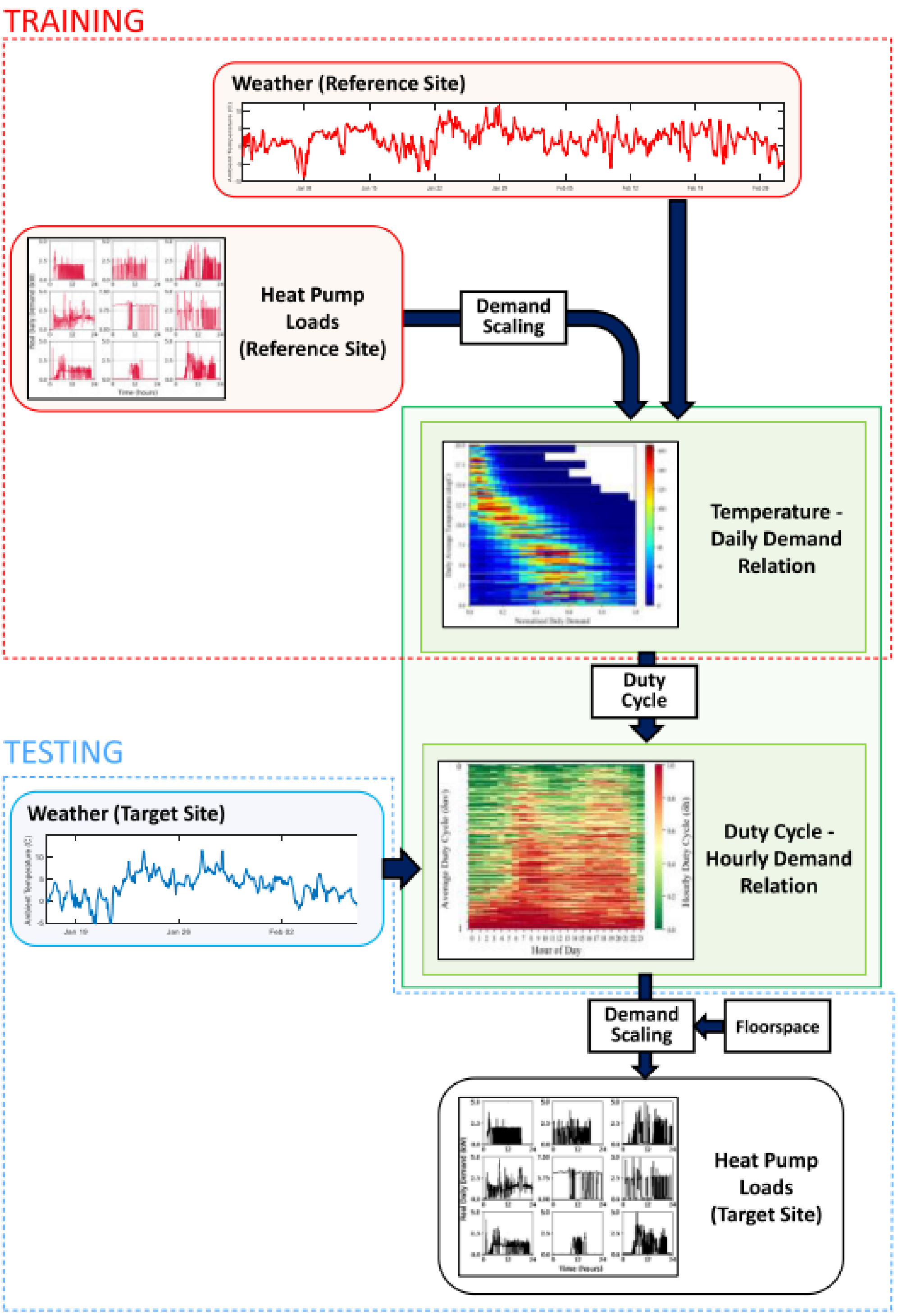


Figure 3-1 Localized Heat Pump Demand Model Overview showing in sample training and out of sample testing/prediction procedures.

This section contributes a method for quantifying the demand impact of increased heat pump uptake for population sizes typical of LV networks, sensitive to local ambient temperature. This is performed by extracting the fundamental relationships between heat pump electrical demand, temperature, and time of day from a training dataset such that it can be applied to a new target application. A one hour-resolution is selected for the synthetic demand profiles as a trade-off between achievability and utility. This one hour-resolution has been selected to focus on examining the steady state effects of electrical heat demand versus external air temperature. One hour is the highest available sampling rate for open-source UK temperature data [132], and examining the effects of electrical demand versus external air temperature change at higher sampling rates would therefore not provide a meaningful result.

This steady state analysis contrasts with examining transient electrical effects such as the start-up current contributed by multiple devices turning on in quick succession and how this might impact network stability.

This model will utilise UK domestic heat pump data coupled with historical weather data in order to characterise the fundamental relationship between daily electrical demand and temperature for heat pumps. This will enable generation of heat pump demand profiles sensitive to local temperature using only the local temperature information and limited inputs to seed the heat pump sizes within the population. The three primary relationships versus ambient temperature this study will characterise are:

• Daily Energy; heat pump electrical demand over the course of a day

• Daily Average Duty Cycle; average heat pump state for a single day

• Hourly Duty Cycle; hourly heat pump state within a single day

Models capturing these relationships are used with local weather observations at a target site to produce a EHP demand for that site; this facilitates modelling hourly heat pump demand for cases independent of the original sample dataset. The interrelationships between model data, characterization and model tests for this work are defined in Figure 3-1. The datasets used for developing this model are described in more detail in section 3.3.1. The model will be validated with multiple datasets, both to prove the concept but also to quantify the error associated with the model.

3.3.1 Case Study Datasets

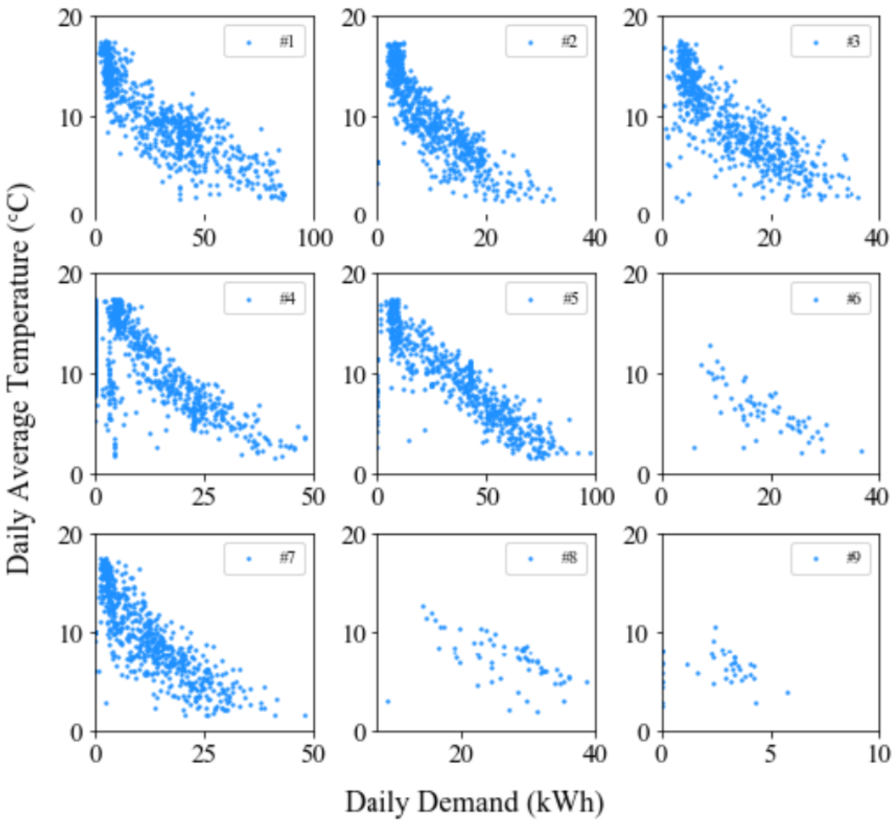


Figure 3-2 Implied joint distributions of daily demand (kWh– x axis) versus daily average temperature (◦C – y-axis) for target data set heat pump loads #1 - #9, taken from [2].

This work makes use of three datasets to model the relationships between demand, temperature, and population size. There is presently no large-scale heat pump dataset available that sufficiently captures all of these parameters; therefore, different data sources are combined in order to define the relationship between heat pump electrical demand and temperature. The reference heat pump demand used for model training is the Renewable Heat Premium Payment (RHPP) dataset [115] features 2-minute resolution electrical demand data collected from 418 air source and ground source heat pumps in the UK from October 2013 to March 2015. This dataset does not feature location data or local weather measurements. The electricity usage monitored in this dataset does not include domestic hot water use which will not be modelled as part of this study. Due to the lack of corresponding local weather data available for individual customers in the RHPP dataset, historical weather data from a climatically average location in the UK is paired with the existing RHPP demand data to complete the reference data set. Historical weather data from the Centre for Environmental Data Analysis (CEDA) for the Central England weather station at Pershore [132] is aligned with the RHPP demand data. Due to the anonymisation process for RHPP customers, it is not possible to link specifically localised weather data to each customer's dataset.

In order to allow for a generalised relationship of local outside air temperature versus electrical demand to be generated, the Pershore weather series is used to give an average view of UK temperature for the corresponding dataset sample period. Pershore weather station is based at an inland, low-lying location in central England and is therefore roughly representative of weather for the majority of the UK population. [133] analysed the relationship between 24 individual meteorological stations throughout the UK and found the correlation between CET monthly temperature means was highly significant ($p < 0.001$), justifying the use of the CET as a benchmark for UK-based climate studies.

Finally, the operational demand data collected during the Low Carbon London (LCL) heat pump trials [2] is used as the target data set for validation purposes. This dataset features electrical heat pump demand and associated local temperature measurements for nine customers; this dataset is used to test that the learned model characteristics produce an accurate predicted heat pump demand from a local temperature measurement. In LCL, customers 1 to 5 and 7 feature two years' worth of data; the remaining customers 6, 8 and 9 only feature 60 days of data. All customers have air-source heat pumps installed with heat pump sizes ranging from 8 to 16kW in rating.

3.3.2 Daily Demand versus Temperature Characterisation

Electric heat pump daily demand is broadly proportional to ambient temperature: lower ambient temperatures translates into higher heat pump daily demand, and vice versa for high ambient temperatures. The influence of parameters such as heat pump rating, efficiency, building insulation type and most importantly occupant routine behavioural parameters result in a range of possible values given a single daily average temperature measurement rather than a single possible value. This is directly observable in the LCL dataset shown in Figure 3-2, with a particularly wide band of possible demand values for 10 ◦C. Customers 6, 8 and 9 are reduced datasets only featuring 60 days of data and therefore only show a partial illustration of this characteristic – they do not capture the full operational variation due to seasonal changes. This relationship is presumed to exist in the RHPP dataset, however is masked by the lack of available corresponding temperature data. This range of possible demand values for a single daily average temperature is the basis for taking a probabilistic approach in this study. In order to create the basis for the model, the hourly demand measurements for each RHPP customer are converted from an hourly advance to daily total in kWh. In order to allow for comparison across the entire dataset, the total daily demand for each customer is normalised with respect to a reference population maxima using the formula:

$$D_{normalised} = \frac{D_{kWh}}{Dmax} \tag{3}$$

where DkWh is the daily demand for a specific day and Dmax is the maximum daily demand for the customer dataset being normalised. This scales all customer data on a range from 0 to 1; 0 representing zero demand and 1 representing maximum demand. The normalised customer demand is mapped to the CEDA Pershore weather station ambient temperature data for the same time period as the training dataset. The training customer demand data and weather data is then unified and plotted in the heatmap shown in Figure 3-3. The aggregated demand data has been split into 1 ◦C intervals and the distribution plotted in Figure 3-3. This clearly illustrates the same characteristic shape as the Low Carbon London data in Figure 3-2; a narrow tail for ambient temperatures above 15 ◦C and a widening band of higher demand for lower temperatures. Datapoints for lower temperatures are sparse in the overall dataset and the increased granularity of the distribution at very low temperatures is visible. The standard deviation and mean is calculated for each of the 1 ◦C dataset intervals,

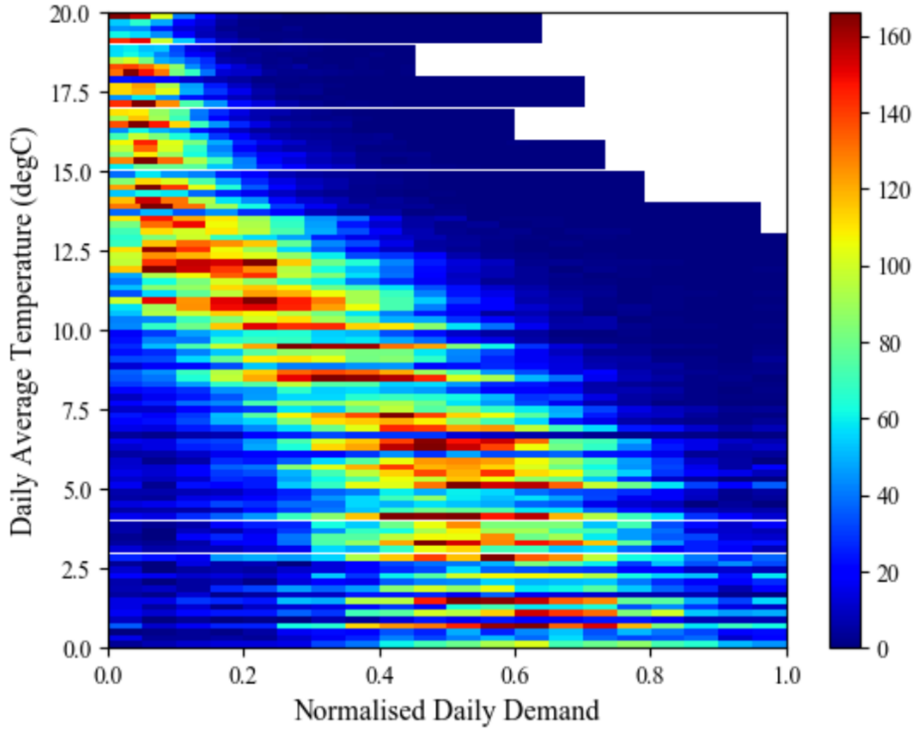


Figure 3-3 Joint histogram showing implied dependency structure of normalized daily heat pump demand against daily average temperature (◦C) from training dataset.

translating the raw data into a Gaussian distribution for each temperature band. This provides a plausible range of normalised demand values for each 1 ◦C interval. This is represented as:

$$f_t(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu_t}{\sigma_t}\right)^2} \tag{4}$$

(4) represents the standard form of a Gaussian distribution, with a temperature specific mean μ_t and standard deviation σ_t, which is obtained for each temperature band in the Normalised Daily Demand versus Daily Average Temperature ◦C relationship illustrated in Figure 3-3. The derived mean and standard deviation parameters are provided in Table 8-1 for reference. Therefore when making a demand prediction the daily average temperature is first identified, and then the demand value is generated based on a distribution determined by the corresponding standard deviation and mean for that temperature that has been derived from the data in Figure 3-3. This represents the conditional distribution as a lookup table consisting of mean and standard deviation, thus removing the need for a fitting a complex functional relation.

$D_{normalised}$ is constructed by obtaining a random sample from the normal distribution defined by the appropriate mean μ_t and standard deviation σ_t parameters for the temperature-band. This random sampling is represented in (5), where N represents normal distribution. The obtained random sample $D_{normalised}$ is scaled into kWh using the formula shown in (5) , where $Dmax$ is the maximum daily kwh demand for the particular EHP.

$$D_{normalised} = \sim \mathrm{N}(\mu_t, \sigma_t^2) \tag{5}$$

$$D_{Predicted(kWh)} = D_{normalised} \times Dmax \tag{6}$$

3.3.3 Daily Duty Cycle

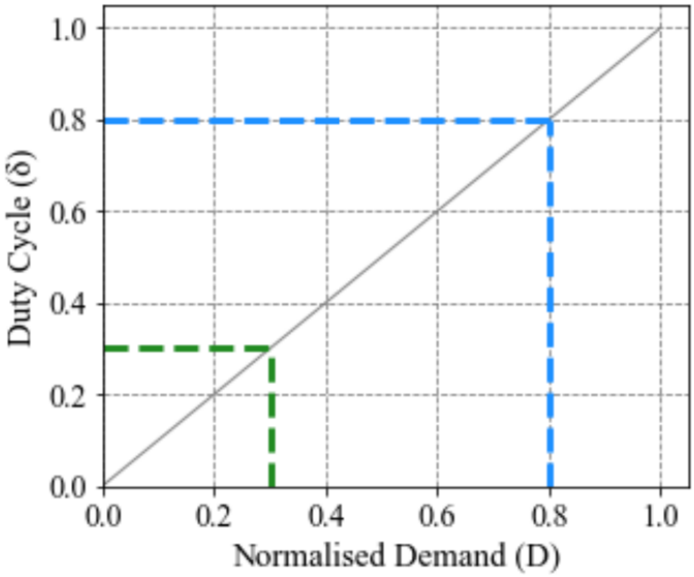


Figure 3-4 Conceptual operating envelope for daily average demand versus daily average duty cycle

A model for predicting daily heat pump energy has been derived however it is still necessary to characterise how this energy is used throughout the day. For this purpose, the modelled duty cycle will be disassociated from time-of-day characteristics. The purpose of this section is to derive the proportion of on and off durations for a particular day, not how heat pump activity is distributed throughout the day. Heat pump outputs can be one of two types: fixed output or inverter based variable output. Fixed output heat pumps operate by cycling on and off between maximum power during the required heating period. Inverter based heat pumps can modulate their output to any intermediate point between zero and full power as required to meet heating demand. Typical fixed output heat pumps operating periods range from 9 to 40 minutes [134], therefore over a time period of one hour the power characteristics of a fixed output versus inverter based output will average to the same profile in order to meet the same heating demand for the majority of cases if conversion efficiencies are assumed to be identical.

Conceptually, therefore the daily average demand is directly proportional to the amount of time the heat pump spends in the ‘‘on’’-state. The ratio of time spent in the on-state versus the off-state will be represented as a duty cycle measure. On this basis this work will develop a two-state model for linking the previously derived daily heat pump energy in section 3.3.2 to an hourly demand figure. The modelled duty cycle δAV is calculated from the ratio of the predicted daily demand DPredicted (kWh) over the real maximum demand Dmax for the customer profile. This is further scaled by duty cycle population data through the value δmax as shown in (7). Each customer profile has their own fixed value of δmax, representing the maximum time the heat pump spends on at the cold operational extreme. The theoretical upper limit for δmax is 1 (representing always on) however the mean δmax obtained from the training population is 0.68, representing a heat pump that is on 68% of the time at its upper operational extreme. The values of δmax are derived from the RHPP population dataset for validation purposes. For an instantaneous sample period heat pumps of any output type can be assumed to be in one of two states: on or off. Under steady state conditions the on-state can be assumed to be fixed, although ramping to steady state will introduce intermediate values of demand. Therefore the daily heat pump demand is directly proportional to the amount of time a heat pump spends on the on-state. Figure 3-4 and (7) illustrate the conceptual relationship between the maximum daily demand Dmax, the maximum daily duty cycle δmax scaling factors, the predicted daily demand DPredicted(kWh) and the derived duty cycle δAV .

$$\delta_{AV} = \frac{D_{Predicted\ (kWh)}}{Dmax} \times \delta max \tag{7}$$

The duty cycle δAV therefore represents the average heat pump state for the daily time period. Once the daily demand DPredicted(kWh) and the daily average duty cycle δAV is known the on-time ton, off-time toff and on-power Pon can be determined. For a single day this is then used to derive the toff, ton and Pon for the heat pump as shown in (8), (9) and (10). This makes the assumption that the heat pump is either fully on or fully off with no intermediate values.

$$t_{on} = (t_{on} + t_{off}) \times \delta_{AV} \tag{8}$$

$$t_{off} = \frac{t_{on} \times (1 - \delta_{AV})}{\delta_{AV}} \tag{9}$$

$$P_{on} = \frac{D_{Predicted(kWh)}}{\delta_{AV}} \tag{10}$$

Figure 3-5 illustrates the relationship between the original observed demand and the modelled demand Pon derived from (8), (9) and (10). The left-hand figure shows the original observed demand over the course of a day; the right hand figure shows the same observed demand dataset but sorted by magnitude rather than plotted versus time. Whilst the observed demand modulates between the on/off state, the actual observed value of Pon varies roughly between 1.5kW to 3.8kW. The simplified modelled demand assumes a fixed kW figure for Pon, that is proportional to the maximum daily demand $D_{Predicted(kWh)}$ and daily average duty cycle δ_{AV}. For the case in Figure 3-5, this modelled demand Pon is calculated as 2.4kW and is plotted alongside the observed Pon, illustrating how derivation of δ_{AV} from $D_{Predicted(kWh)}$ can be used to model a good approximation for the proportion of time a heat pump spends in either the on or off state. The distribution of the modelled on/off states for a single day are derived in the next section.

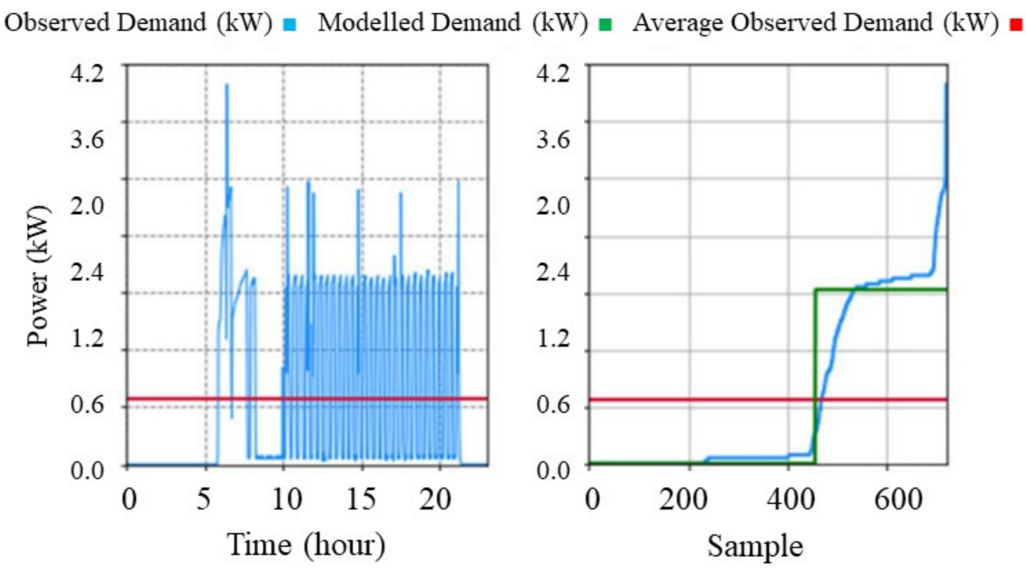


Figure 3-5 (left) Observed Demand (kW), (right) Modelled Demand (kW) and Observed Demand (kW) for single day.

3.3.4 Hourly Duty Cycle

The remaining aspect of the model is to develop a method for determining heat pump hourly demand profile from the daily average energy and daily average duty cycle. As illustrated in Figure 3-2 the shape of a daily electrical demand profile can vary significantly from household to household due to heat pump and building parameters, as well as behavioural routines. The primary concern around heat pump type loads is that without a storage element to buffer or shift time of use, heat pump loads can be anticipated to be needed at similar times of day for most households, in combination with their high energy and high-power characteristics. Therefore, the specific time of day for heat pump activity becomes of critical interest – a load that is distributed evenly throughout the

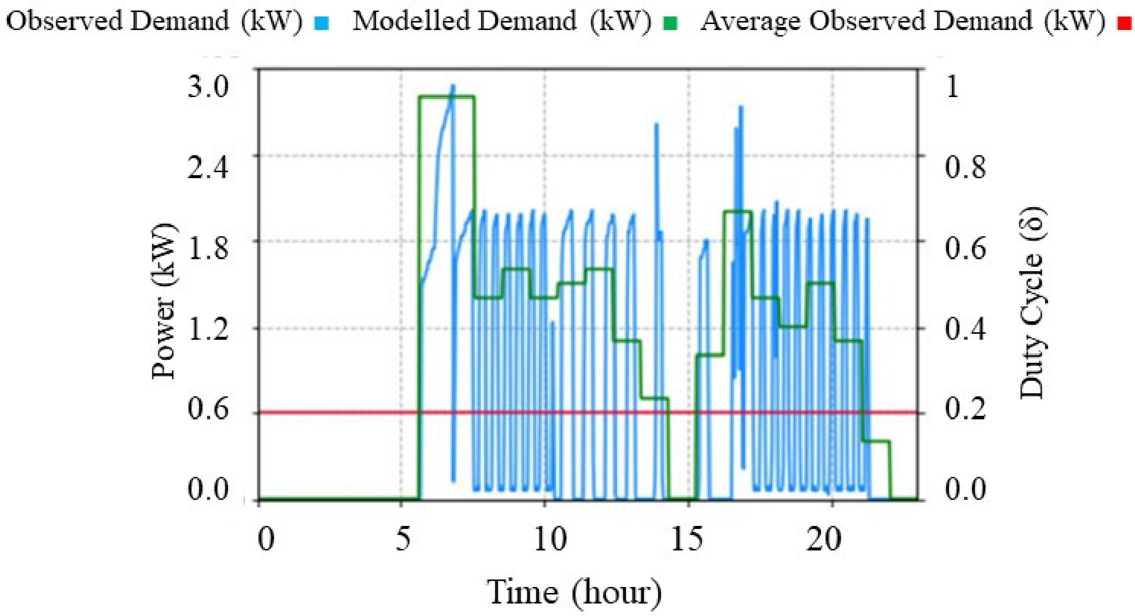


Figure 3-6 Real demand (kW, blue), modelled duty cycle (green) and average real demand (red)

day will not pose the same risks to voltage and thermal limits as a load that tends to be clustered around existing the domestic load peaks in the morning and evening. The time of use patterns across the entire RHPP dataset will be characterised and then fed back into a validation model. Ideally power would be modelled as an instantaneous value, however due to the variability in heat pump type and operation, it is not possible to develop a high-resolution predictive model that is fully applicable for the entire dataset. The approach here is to therefore develop a practical method for characterising sub-daily demand magnitudes to a reasonable resolution for network-based analysis and validation. The aim of this model is not to detect or characterise fast transients (which are better predicted by physics-based models), but rather steady state network conditions and how they contribute to network limits. This work will therefore model hourly demand magnitude rather than instantaneous power. Further work would be possible to reduce this time resolution further for specific applications. It has been shown in section 3.3 that modelling a linear relationship between the daily demand and daily average duty cycle δ_{AV} through (7) allows for derivation of the t_{on}, t_{off} and P_{on} values for a particular day. This section will outline a framework for linking the derived daily average duty cycle to a set of hourly duty cycle values determined by ambient temperature. This set of hourly duty cycles will retain the overall predicted t_{on}, t_{off} and P_{on} values determined by the δ_{AV} for a particular day. The individual time of day versus temperature relationships for all RHPP customers will be aggregated into a single framework that can be used to generate synthetic demand profiles. Figure 3-6 illustrates a sample raw demand profile translated into daily and hourly duty cycle for a single customer.

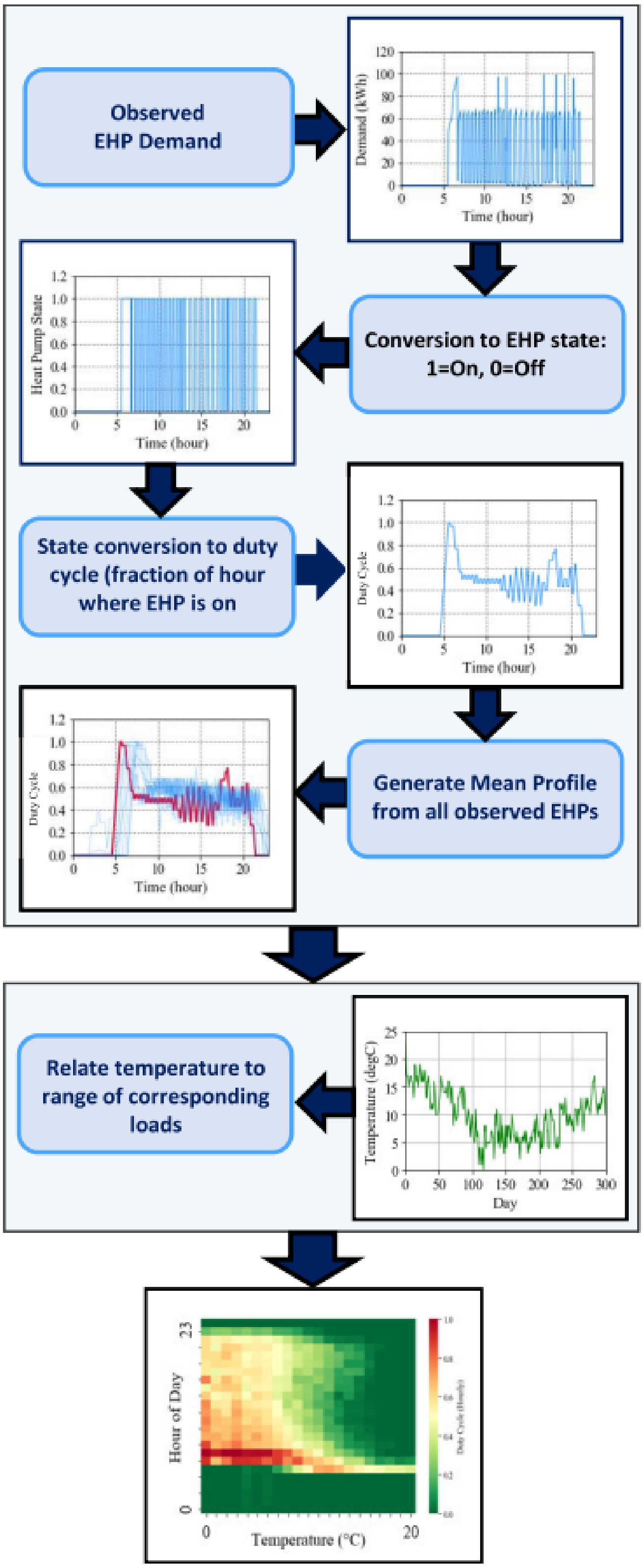


Figure 3-7 Conditioning of raw heat pump electrical demand profile into time of use profile versus temperature

3.3.5 Heat Pump Demand from Temperature Translation Model

This section describes the process for translating the daily average duty cycle δ_{AV} into a corresponding set of hourly duty cycle values, allowing for shaping of an overall daily demand profile. Building on the relationship between daily demand and daily duty cycle defined in section 3.3.4, for all daily customers the raw load profile is translated into an hourly duty cycle and temperature profile relation. Due to the direct relationship between heat pump energy consumption and ambient temperature, the time of use characteristics for a particular heat pump will also vary with temperature – heat pump activity during the day reduces with warmer temperatures and vice versa for cold temperatures. The output of this conditioning stage is that for each unique customer there exists an aggregated duty cycle profile for each hour of the day and temperature combination dataset The data conditioning process to transform the raw demand data into a daily average temperature versus hourly duty cycle profile is outlined graphically in Fig.8. For each customer, the raw demand profile for each 1◦C slice is converted to instantaneous heat pump state as shown in (11), where Emax represents the maximum instantaneous demand magnitude for the day. This is then converted to hourly duty cycle. The process to convert the raw kWh/2mins measurements $E(t)$ into the averaged hourly duty cycle is given in (9). The factor of 30 is the number of measurements required to sample a one-hour period due to the two-minute sampling rate in the raw trial data. Finally, all profiles belonging to the same customer and 1◦C temperature set are averaged to create an aggregated profile of hourly duty cycle versus temperature through (13), where n represents the number of datasets available for a particular customer and 1 °C temperature combination. This final figure δ_h then provides a single average hourly duty cycle δ_h for a customer, drawn from the aggregate of a customer's raw data and corresponding δ_{h_n} for a particular hour of day ranging from 0 to 23. This process does not make any distinction between weekend, weekday, or any exceptional days such as holidays or bank weekends. The impact of the weekday/weekend distinction on modelling strategies has been assessed in [135], which identifies clear changes in load routines during weekdays versus weekends. The aim of this work however is to first develop a generalised model that can then be tailored to suit specific analysis tasks.

$$E(t) = \begin{cases} 1 \ t > 0.1\ (Emax) \\ 0 \ t < 0.1\ (Emax) \end{cases} \tag{11}$$

$$\delta_{h\_n} = \frac{1}{30} \sum_{t}^{t+29} E(t) \tag{12}$$

$$\delta_h = \frac{1}{n} \sum_{1}^{n} \delta_{h\_n} \tag{13}$$

Each customer therefore has a 24 x 20 array where there is a row associated with each hour of the day and a column associated with each 1°C temperature slice, with each cell representing an hourly duty cycle δ_h that reflects the heat pump activity for those conditions. The array is defined as follows for each customer:

$$\delta_h = f(temperature, hour\ of\ day) \tag{14}$$

The final output of this process is shown at the bottom of Figure 3-7 as the hour of day versus temperature plot. This shows an example of a time versus temperature relationship for a single customer. Figure 3-8 shows a further selection of temperature versus time of use profiles for nine additional customers: this clearly illustrates the diversity in time versus temperature relationships for multiple customers. From this limited selection it can be seen that customers tend to retain heat pump behaviours across the temperature range. Customers that do not enable heating during the day for cold extremes tend not to enable heating for any other temperature. Similarly, customers that have heating operating continuously at cold extremes still exhibit this behaviour at warmer temperatures.

3.3.6 Daily to Hourly Demand Relation Learning

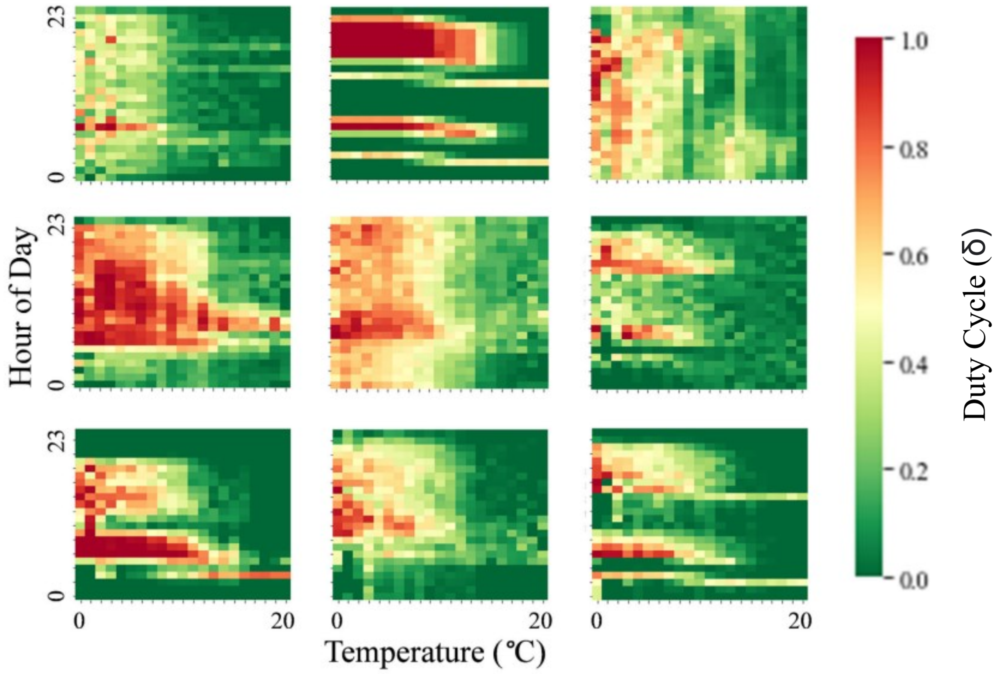


Figure 3-8 Selection of nine customer temperature versus time of use profiles from training dataset

This section will further condition the data in order to link sets of hourly duty cycles to a single daily average duty cycle figure and therefore shape a demand curve based on a single daily average duty cycle value. Each of the 418 temperature versus time of day profiles derived from the RHPP dataset and defined in (14) are combined into a three-dimensional array defined as:

$$\delta_h = f(temperature, hour\ of\ day, customer) \tag{15}$$

The customer axis is transformed into a numeric δav value by computing the average daily duty cycle for each customer and temperature set of 24 δh values:

$$\delta_{av} = \frac{1}{24}\sum_{0}^{23}\delta_h \tag{16}$$

The array in (15) is now modified with the customer axis being replaced with the δav corresponding figure calculated in:

$$\delta_h = f(temperature, hour\ of\ day, \delta_{av}) \tag{17}$$

Finally, this array sorted by average daily duty cycle. This sorts the array by heat pump activity for the entire population sorted by most active to least active. Figure 3-9 shows the 0◦C slice of this array. This array shows the distribution of heat pump activity across the entire RHPP population versus time of day. Clear morning and evening peaks are visible, but there are also customers with very high and very low heat pump activity at either extreme. This array clearly illustrates that heat pump activity exists on a continuum rather than there being clearly defined repeating profiles. It is theorised that this characteristic will be true for all UK based heat pump populations over a certain size that feature a certain level of diversity. The subsequent temperature slices in Figure 3-10 clearly show the reduction in heat pump activity with temperature. The onset of the

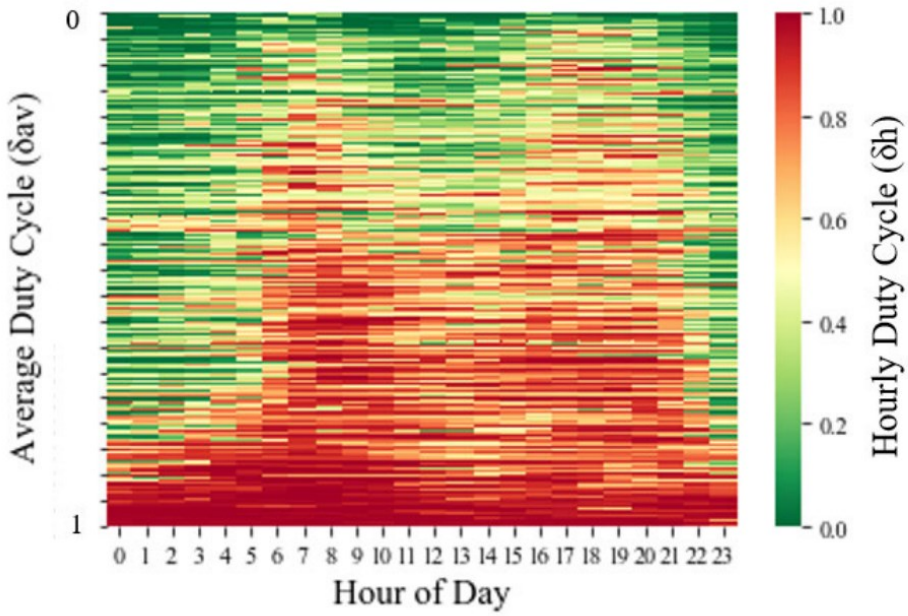


Figure 3-9 Heat Pump Hourly Duty Cycle (0 to 24 hours, x-axis) versus Average Duty Cycle (y-axis)

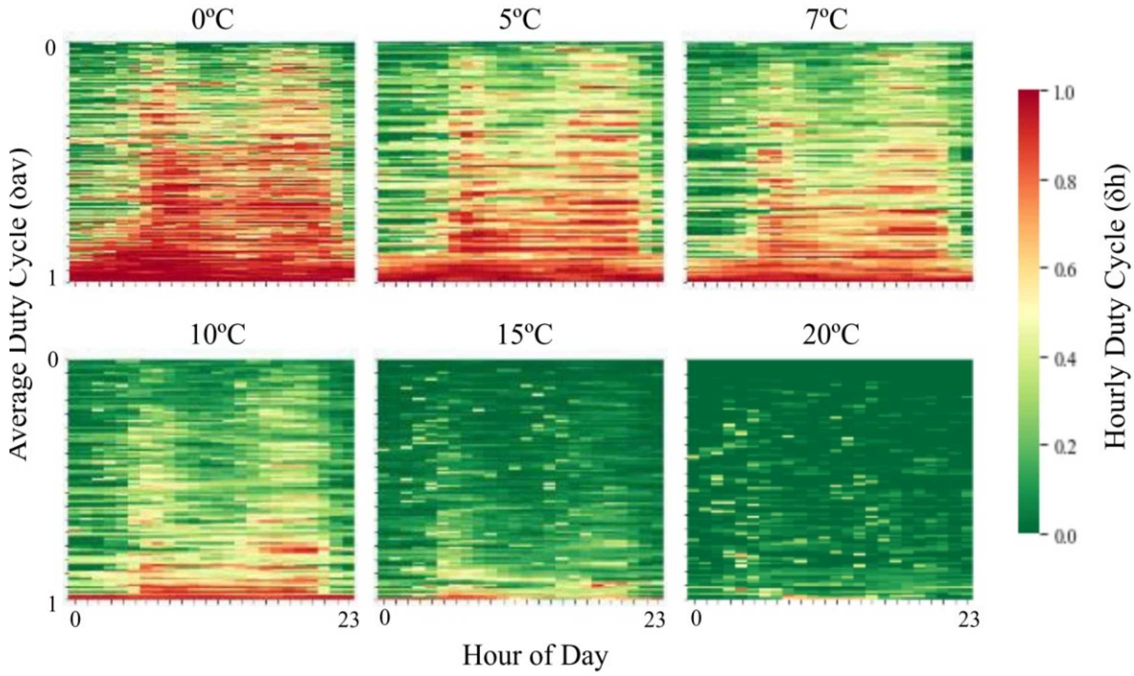


Figure 3-10 RHPP Heat Pump Hourly Duty Cycle Distribution - (0 to 24 hours, x-axis) versus Average Duty Cycle (y-axis) for 0◦C, 5◦C, 7◦C, 10◦C, 15◦C and 19◦C

morning demand peak at 6am and drop off at 10pm correlates closely with the December averaged profiles obtained from the Customer Led Network Revolution heat pump study, which consisted of 89 customers [108]. It is now possible to generate an hourly demand estimate using only a daily average temperature input combined with the demand and duty cycle linear scaling factors. The daily demand is generated as per the relationship shown in Figure 3-2. From this an hourly duty cycle can be obtained through the relationship between hour of day and daily average duty cycle shown in Figure 3-10. Finally the daily average duty cycle is paired with the closet matching set of hourly duty cycles for the appropriate temperature in (14). The predicted hourly demand $D_{predicted\_h}$ for each hour of the day being calculated is obtained though (15):

$$D_{predicted\_h} = \delta_h \times \frac{D_{predicted(kWh)}}{24} \tag{18}$$

where $D_{predicted\_h}$ (kWh) is the predicted daily power and δ_h is the predicted hourly duty cycle. Fig.12 illustrates the final load profile output of the process for a single theoretical customer and range of temperature values.

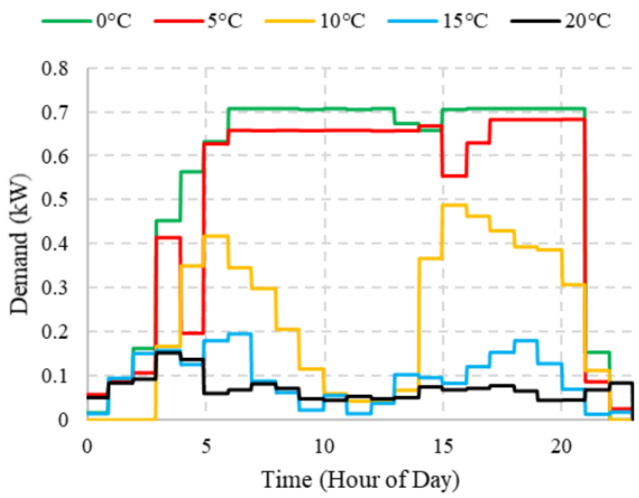


Figure 3-11 Daily demand profiles for a single customer for 0◦C, 5◦C, 10◦C, 15◦C and 20◦C

3.3.7 Training Dataset – Customer Profiles

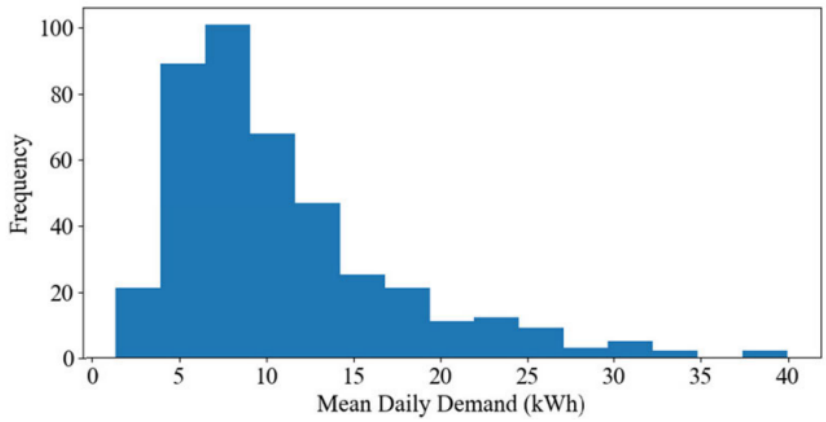


Figure 3-12 Distribution of RHPP Customers by mean heat pump daily demand (kWh)

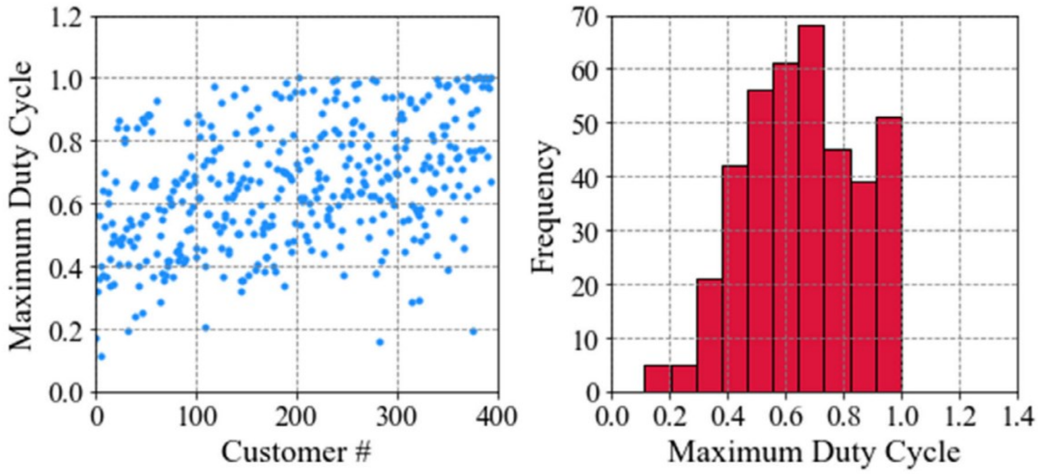


Figure 3-13 (left) Maximum duty cycle versus customer # (right) Distribution of maximum duty cycle for RHPP customer dataset (kWh)

The RHPP training dataset acts as the source of scaling factors for daily demand D_{max} and duty cycle δ_{max} in this study in (23) and (7). The structure of this model is such that the model may be seeded with scaling factors from other populations or datasets as required for specific analysis. This section describes the general population characteristics of the scaling factors used within this study. The limitations of using the RHPP dataset method have been identified in previous works – customers in the RHPP dataset are predominately local authority landlords rather than private tenants [76]. Additionally, heat pump technology has advanced since the installation of the sample population hardware in 2013 and therefore this may not fully be representative of a modern population due to improvements in achievable COPs and building efficiencies. The normalised demand generated in section 3.3 is multiplied from the scaling factor D_{max} derived from the RHPP population demand magnitude. Figure 3-12 illustrates the mean daily demand for each customer across the RHPP dataset. The population predominately features customers at the lower end of the mean daily demand.

The maximum duty cycle δ_{max} per customer in the RHPP dataset is shown in Figure 3-13. This shows that apart from customers with very low heat pump demand, maximum duty cycle is not strongly correlated to heat pump demand and is distributed normally throughout the dataset. The right-hand side of Figure 3-13 shows that maximum duty cycle is approximately normally distributed throughout the RHPP dataset.

3.4 Validation of Predicted Demand Profiles

The developed model is validated against the observed demand data in the RHPP training dataset and the LCL target dataset. The model is fundamentally derived from training dataset characteristics and therefore the tests versus the LCL dataset validate how well the method works versus unseen data. Large scale population testing is performed with the training dataset, using the user profiles and demand shapes generated from the training dataset. The inputs used to generate a demand prediction are for a single day are the daily average demand, and the customer scaling factors: maximum daily demand Dmax and maximum daily duty cycle δmax. These inputs are then fed into the thermal relations derived in this paper in order to generate daily and hourly demand predictions. Random populations of customers ranging from 1 to 160 are used; with the error being assessed as a simple mean absolute percentage error from 0◦C to 15◦C. Heat pump behaviour below 0◦C is beyond the scope of this model due to the lack of data for this condition in the used datasets; beyond 15◦C is not examined as beyond this point heat pump activity becomes minimal in the real data in terms of energy as shown in Figure 2-1Figure 3-3.

3.4.1 Daily Demand Testing

	0°C		5°C	
#	MAPE (%)	σ_d (%)	MAPE(%)	σ_d (%)
1	38.6	43.3	82.9	285.9
5	23.7	23.1	21.4	18.6
10	17.0	13.8	18.7	13.7
20	15.1	11.4	15.1	8.9
40	12.1	7.2	13.9	8.8

80	12.6	4.6	13.2	4.9
160	12.6	3.2	12.3	3.2

	10°C		**15°C**	
#	MAPE (%)	σ_d (%)	MAPE (%)	σ_d (%)
1	82.8	230.0	68.3	109.4
5	20.8	18.6	24.6	20.6
10	16.3	10.8	18.5	13.3
20	13.2	8.9	12.5	8.8
40	13.0	8.1	11.0	7.9
80	12.3	4.5	8.4	4.8
160	12.8	3.4	7.6	5.5

Table 3-1 Daily demand prediction mean absolute percentage error (MAPE) and its standard deviation for 0, 5, 10, 15°C and aggregations of 1, 10, 20, 40, 80, 160 customers using training dataset.

	Target Local Weather		**Pershore CEDA Weather**	
#	MAPE (%)	σ_d (%)	MAPE (%)	σ_d (%)
9	14.4	8.1	18.6	11.1

Table 3-2 Daily demand MAPE and its standard deviation for target customer dataset using target local weather and Pershore CEDA weather observations

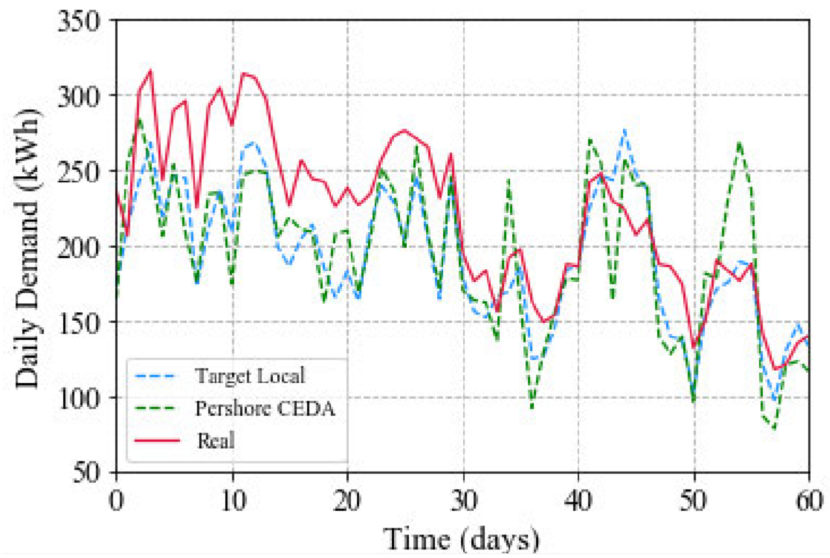


Figure 3-14 Real Demand, Predicted Demand (Target Local Weather) and Predicted Demand (Pershore CEDA Weather) for 9 aggregated LCL customers from 7/01/2014 to 20/03/2014.

The real versus predicted daily demand is calculated for randomly selected groups of 1, 5, 10, 20, 40, 80 and 160 customers. For each size group, a random selection of customers is selected from the training dataset and the real daily demand versus predicted daily demand calculated. This process is replicated 100 times for each group size in order to obtain a mean and standard deviation for error, with a new random selection of customers generated each time. 100 runs per customer group is chosen as a trade-off between computing time and accuracy. From this the mean absolute percentage error for each customer in each group is calculated as shown in, where Dreal_d is the real daily demand and Dpredicted_d is the predicted daily demand as derived from (5) . This process is then repeated for the temperature points 0◦C, 5◦C, 10◦C, and 15◦C. The final MAPE for each temperature/group number combination is simply the average MAPE obtained for each set. The percentage standard deviation σ is calculated as per (20). The results for this process are shown in Table 3-1.

$$MAPE = \sum \left| \frac{D_{real\_d} - D_{predicted\_d}}{D_{real\_d}} \right| \times 100 \tag{19}$$

$$\sigma_d = \sqrt{\frac{\sum(D_{predicted_d} - \mu)^2}{n}} \tag{20}$$

For the target dataset there are nine customers and the maximum overlap in time for the overall dataset is a 60-day period ranging from 17/01/2014 to 20/03/2014. The aggregated customer demand from this period is used to evaluate the training dataset derived model for predicting demand for other customer datasets. Two temperature profiles are used to synthesise the daily demand: one is the Pershore weather dataset used for the training dataset, the second is the averaged local temperature data from the target dataset. Figure 3-14 shows the real versus predicted daily demand for the aggregated target data profile over a two-month winter period. Table 3-2 demonstrates MAPE = 14.4% with σ_d = 10.8% for the 9 LCL customer winter case, whereas Table 3-1 for 10 RHPP customers on a 0°C day resulted in MAPE = 17.0% with σ_d = 13.8% . This can be attributed to the fact that the Pershore weather data does not reflect the local ambient temperature conditions for the target dataset customers, which are distributed throughout the south-east of England. However, this result does illustrate that the normalised demand versus temperature relationship derived from the training dataset shown in Figure 3-3, combined with a simple scaling factor is able to achieve good results for daily demand for small heat pump population even with a non-local temperature series. The MAPE and σ modelled using the Pershore weather dataset in Table 3-2 align well with the corresponding training dataset error values in Table 3-1 for population sizes of 10.

3.4.2 Hourly Demand Testing

There are several features of interest when examining the shape of a daily demand profile for network design and operations. The magnitude of the demand peak, the time of the demand peak, in addition to maximum rates of change are all of interest when assessing network impact, however this list is not exhaustive. The MAPE method used in the previous section is not suitable for measuring the shape quality; small values feature heavily in the dataset at higher temperatures and large errors in small hourly demands which can skew the whole figure. In order to overcome the skew that would exist with a conventional MAPE, a weighted MAPE is used. This WMAPE is weighted by the sum of total real demand for a given day and is calculated as shown in (21), where Dreal_h is real hourly demand, and Dpredicted_h is the corresponding predicted value of demand for the same hour generated from (18). The WMAPE gives a general metric of predictive accuracy but does not explicitly assess the predicted demand peak or the predicted time of the demand peak versus the real values as part of this study.

$$WMAPE = \frac{\sum_{h=0}^{23} \left| D_{real\_h} - D_{predicted\_h} \right|}{\sum D_{real\_h}} \tag{21}$$

$$\delta_h = \sqrt{\frac{\sum (D_{real\_h} - D_{predicted\_h})}{\sum D_{real\_h}}} \tag{22}$$

Table 3-3 Hourly demand WMAPE and its standard deviation for 0, 5, 10, 15◦C and aggregations of 1, 10, 20, 40, 80, 160 customers using training dataset.

	0°C		5°C	
#	WMAPE (%)	σ_h (%)	WMAPE (%)	σ_h (%)
1	66.1	14.7	68.5	16.8
5	37.4	7.7	37.7	6.9
10	27.0	5.8	31.2	5.3
20	20.1	3.7	29.7	4.1
40	15.6	3.1	17.4	3.9
80	13.1	2.2	14.6	4.7
160	11.6	2.0	13.6	2.1

	10◦C	15◦C

#	WMAPE (%)	σ_h (%)	WMAPE (%)	σ_h (%)
1	81.3	13.7	87.1	9.0
5	50.2	7.3	69.9	7.0
10	38.3	5.6	58.1	6.6
20	31.2	4.1	47.7	5.1
40	24.0	4.0	38.2	3.7
80	17.9	4.7	32.3	2.9
160	14.6	2.2	27.2	2.2

	Target Local Weather		**Pershore CEDA Weather**	
#	WMAPE (%)	σ_h (%)	WMAPE (%)	σ_h (%)
9	35	13.1	37	15.6

Table 3-4 Hourly demand WMAPE and its standard deviation for target customer dataset using target local weather and Pershore CEDA weather observations

3.5 Model Performance Evaluation

The proposed model in this study has outlined a simple approach for predicting daily and hourly heat pump demand profiles for a user-defined sample population, using only daily average temperature and linear scaling factors as inputs. The performance of the model against two independent datasets have been examined in order to evaluate the wider applicability of this model for UK based heat pump population, with consistent results across both the training RHPP and target LCL datasets. Whilst constrained by the lack of further available heat pump demand data to examine this point further, these initial results do indicate that the derived model will be applicable in general for UK customers. As illustrated in Figure 3-11 and Figure 3-14 the model offers good capability for predicting the magnitude of daily demand for heat pump populations for operating conditions ranging from 0◦C to 15◦C. The mean daily demand error reduces as temperature increases; this is in line with the dependency relationship plotted in Figure 3-3 which features a smaller band of possible values for higher temperatures when compared to cold temperatures. In contrast, the mean error for hourly demand increases with temperature. This can be attributed to the greater diversity in demand shape at warm temperatures as users are more likely to transition to only operating heating for limited time windows. The general error characteristics for both the daily and hourly demand tests reflect findings of previous LV studies which observed strong scaling relationships between the number of households and MAPE of a forecast method [136]. Whilst there are no directly comparable heat pump studies using MAPE that the results of this work can be compared against, it can be broadly compared with existing LV studies forecasting other load types. Previous works forecasting LV substation loads using have achieved MAPE's in the region of 11%–16% utilising ARIMA methods [137] [138]. While the model contributed here is a predictor of load from temperature, it could offer a forecasting capability if used in conjunction with a temperature forecast from a numerical weather prediction model. Typically forecasting temperature yields lower errors than demand so the anticipated heat pump demand forecast error would be broadly aligned with this figure. The demand activity peaks shown in Figure 3-8 and Figure 3-10 are in agreement with the demand peaks of averaged heat pump demand data from a comparable but geographically separate trial [108]. Whilst limited in size compared to the overall training dataset, the results for the target population show consistent error results when compared with the RHPP error for groups of a similar size. This does suggest that the RHPP derived characteristics for the demand and demand shape model will be widely applicable for UK households. As has been shown, heat pump electrical demand magnitude is highly sensitive to temperature. Whereas existing works tend to focus on the demand impact of heat pumps for the extreme cold case [87] [113] [78], this work facilitates the generation of representative heat pump demand profiles ranging from 0◦C up to 20◦C. Given the increased penetration of low carbon technologies (LCTs) on LV networks, it becomes of increased importance to model the combined effects of LCTs alongside conventional loads rather than study the extreme case for one technology type in isolation. The future LV power system will need to be safely rated to incorporate the effects of photovoltaics, wind, and electrical vehicles in addition to low-carbon heating. The temperature sensitivity of this model allows for generation of demand profiles for any seasonal condition rather than the extreme case, enabling study of heat pump effects alongside other technologies. Table 3-4, which uses local weather data, illustrates a noticeable effect on the final error of a demand forecast. A typical winter day is therefore expected to be different in shape and magnitude depending on the local climate extremes – the model presented can generate locally specific demand profiles alongside a quantified error, rather than using an extreme winter case not tailored to local conditions. Whilst this model captures the behavioural time of use relationship that is typically absent from physical models, there are certain pre-requisites to consider when using this method to predict electric heat pump demand. In particular, this model is dependent on source user profiles in order to seed appropriate scaling factors when performing demand normalisation and a proxy for these on de-normalisation. The scaling factors used in this study are contemporary to the capabilities of heat pump technology at the time of the original study. In order to revise these scaling factors for future generations of hardware, these values would have to be adjusted in taking into account typical COP's and critical physical parameters for new hardware. Scaling factors will inevitably be a function of building parameters such as floor area, building layout and insulation efficiency as well as heat pump rating, itself related to the latter parameters. Building floorspace has been shown to have the greatest influence on household heating demand [139]; a potential opportunity for further work would be to derive building characteristics including floorspace from remote imagery or aerial lidar data in order to automatically define scaling factors tailored to a local area [140]. It has not been possible to model the effects of heat pump demand below 0◦C due to the very limited availability of data from this extreme operating region. Below 0◦C the COP of conventional EHP’s drops off significantly, greatly reducing conversion efficiency [141]. The typical mitigation strategy to counter this behaviour is to install secondary resistive heating to supplement the heat pump output for extreme cold cases. This raises the threat of yet higher demand peaks that are driven by outdoor air temperature and would require a second model to incorporate the load characteristics of this behaviour.

The developed model is constructed and tested using a combination of RHPP [115] and Low Carbon London [2] trial data, which concluded with data collection in 2017 and 2015 respectively. In addition to being reflective of domestic EHP technology at the time, the recorded electrical heat pump demand will reflect the characteristics and the severity of the cold weather conditions during the trial sampling periods. Neither trial overlapped with the extreme weather events of the 2018 British Isles cold wave [142], or the less recent 2008 ‘Beast from the East’ which saw temperatures of -14.2°C in parts of south-east England [143]. In contrast to these more extreme winter events, the Met Office provisionally declared 2023 as the warmest year ever for the UK for minimum temperature [144]. On top of these climatic considerations, the exceptionally high cost of energy has seen estimated drops in household gas and electricity consumption by 10.8% and 8.4% respectively [145].

Therefore, the raw trial data does not provide insight into how domestic EHP’s may respond at the coldest winter extremes, but consideration must be additionally given to the ongoing drift and rapidly evolving changes in the climate of the United Kingdom as well as the economic context in which households use energy. The climatological and economic context of the original trial data should be considered when seeking to apply this methodology to further EHP impact studies.

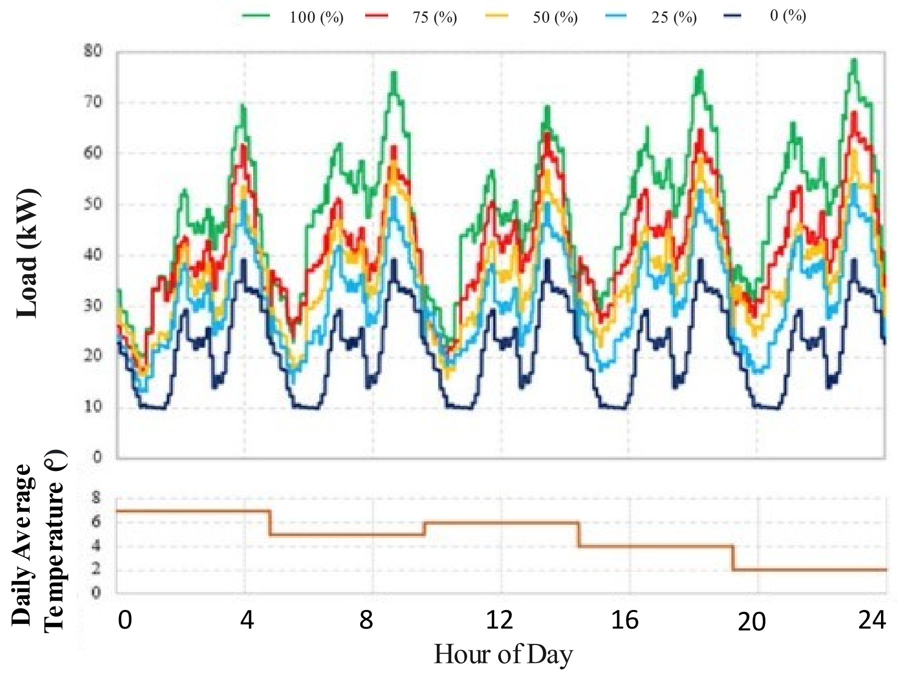


Figure 3-15 Distribution network feeder load for 0%, 25%, 50%, 75% and 100% EHP penetration on 40 customer residential network during five day winter period (a-top) and corresponding daily average outdoor air temperature (b-bottom)

Through the development of a EHP-specific load model, this work facilitates the further analysis of EHP impact on LV networks both in isolation, and alongside the effects of other low-carbon technologies. The method could be used for a range of applications including examining EHP penetration network impact, as part of a demand response analysis or as part of mixed-energy network studies. The probabilistic approach allows for confidence intervals to be defined alongside a load prediction; these could be derived from the relevant MAPE and σ in Table 3-1 and Table 3-3. This complements existing probabilistic approaches for other LV-connected low carbon technologies [146]. It is therefore envisioned that this heat pump specific model could be used alongside other probabilistic load types in order to thoroughly examine possible network conditions in the presence of load and generation uncertainty. The main challenge EHPs present is the effect at scale at the last mile of distribution networks. Underground cables at this part of the network accounts for a significant volume of the assets of a network owner and replacement or reinforcement of these to accommodate EHP load may require an investment beyond their capabilities. As an example application, the predictive model is used to model a simple power flow scenario for a single LV feeder with 40 connected households and varying levels of EHP penetration. Smart meter data from the Low Carbon London trials [147] is used to create a base domestic load and combined with increasing levels of EHP penetration on the feeder. Heat pump electrical demand is then predicted for an artificial five-day winter period; Figure 3-15 illustrates the output of this study.

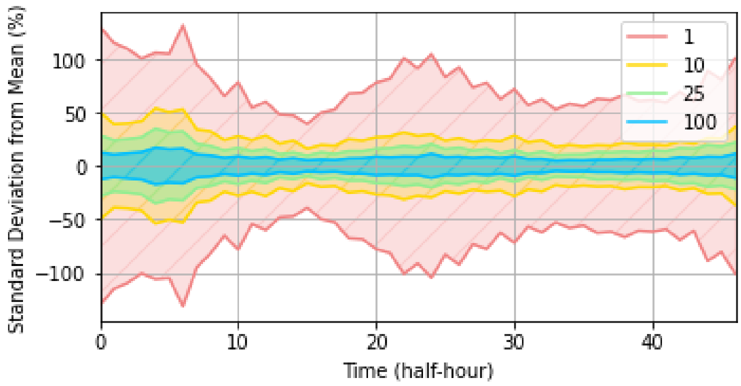


Figure 3-16 Uncertainty versus Time of Day versus Number of Customers

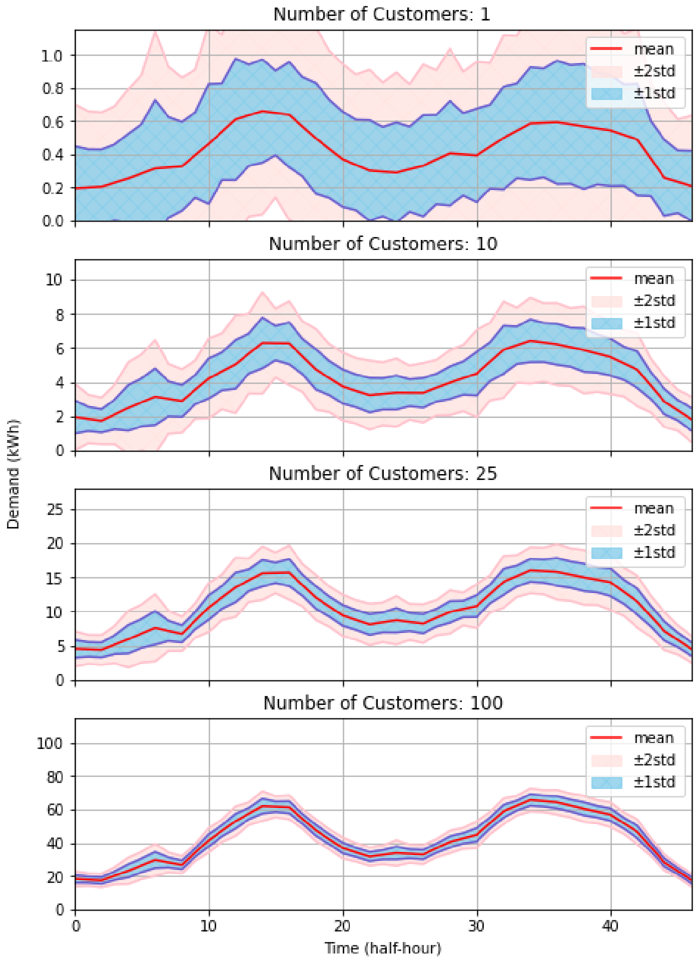


Figure 3-17 Mean demand and standard deviation for 1, 10, 25 and 100 customers

The fundamental shape of the overall load profile does not significantly change between the 0% and 100% penetration cases; the morning and afternoon peaks are roughly concurrent for all levels of penetration however the morning peaks additionally get wider. However, the magnitude of the daily load peaks can be seen to significantly increase in value, with the evening peak approximately doubling in value for the 100% case. This agrees with the expectation outlined at the outset of this paper that full heat pump penetration is roughly equivalent to doubling the number of households on a network.

Figure 3-16 and Figure 3-17 demonstrate the effects of uncertainty versus time of day for groups of 1, 10, 25 and 100 customers. For each customer group of n size, 100 random selections have been made from the load profiles developed in 3.3.5 for the °C case and the average standard deviation from the mean demand calculated. For Figure 3-16 there is increased confidence, or reduced standard deviation from mean demand, for an increasing number of customers. The two lowest troughs of uncertainty roughly correspond to the morning and evening spans of time where heating activity is typically highest for a household.

Figure 3-17 demonstrates the same results but plotted versus kWh rather than % standard deviation from mean. Each of the customer group cases displays a roughly similar load shape throughout the day, but the uncertainty for any time of day rapidly diminishes for increased number of customers.

These results are drawn from the load profiles generated from the RHPP dataset therefore these profiles provide an average view of electrical heat demand and uncertainty. For a real-world feeder with several households of similar construction, occupant demographics and thermal routines, there may be reduced diversity versus the averaged RHPP case.

3.7 Conclusion

This chapter has defined a model for quantifying the demand impact of increased uptake of electric heat pumps for population sizes representative of typical LV network applications using demand relationships derived from existing operational datasets and sensitive to local weather conditions. A generic relationship between heat pump electrical demand and outdoor air temperature has been identified from real customer data and validated on two independent datasets. This model facilitates the analysis of heat pump demand that is sensitive to local outdoor air temperature conditions, rather than blanket rescaling of existing customer data as has been performed for previous studies, augmenting the utility of sparsely available demand data. By using a probabilistic approach, the distribution of prediction error has been quantified. This creates future opportunities for examining heat pump demand sensitivity for different geographical locations against existing heat pump assessments, as well as performing studies which incorporate multiple low carbon technologies connected to a LV network. The main priority for further work would be to relate the magnitude of electrical demand to an estimated

COP and nameplate heat pump rating, such that the scaling factors used for the model could be modified to accommodate improvements in heat pump efficiency. It would additionally be of interest to examine the variation in weekday, weekend, and exceptional events.

Chapter 4

Scale Localisation of Electrical Heat Demand for LV Distribution Networks using Geospatially Linked Gas Demand Data

This chapter presents a novel localisation electrical heat load model, overcoming the limitations of highly aggregated electrical heat load profiles in order to develop load profiles that are sensitive to geospatially variable factors such as building physical parameters and individual demographics. The impact of localisation is demonstrated via ADMD and through a feeder case study.

4.1 Introduction

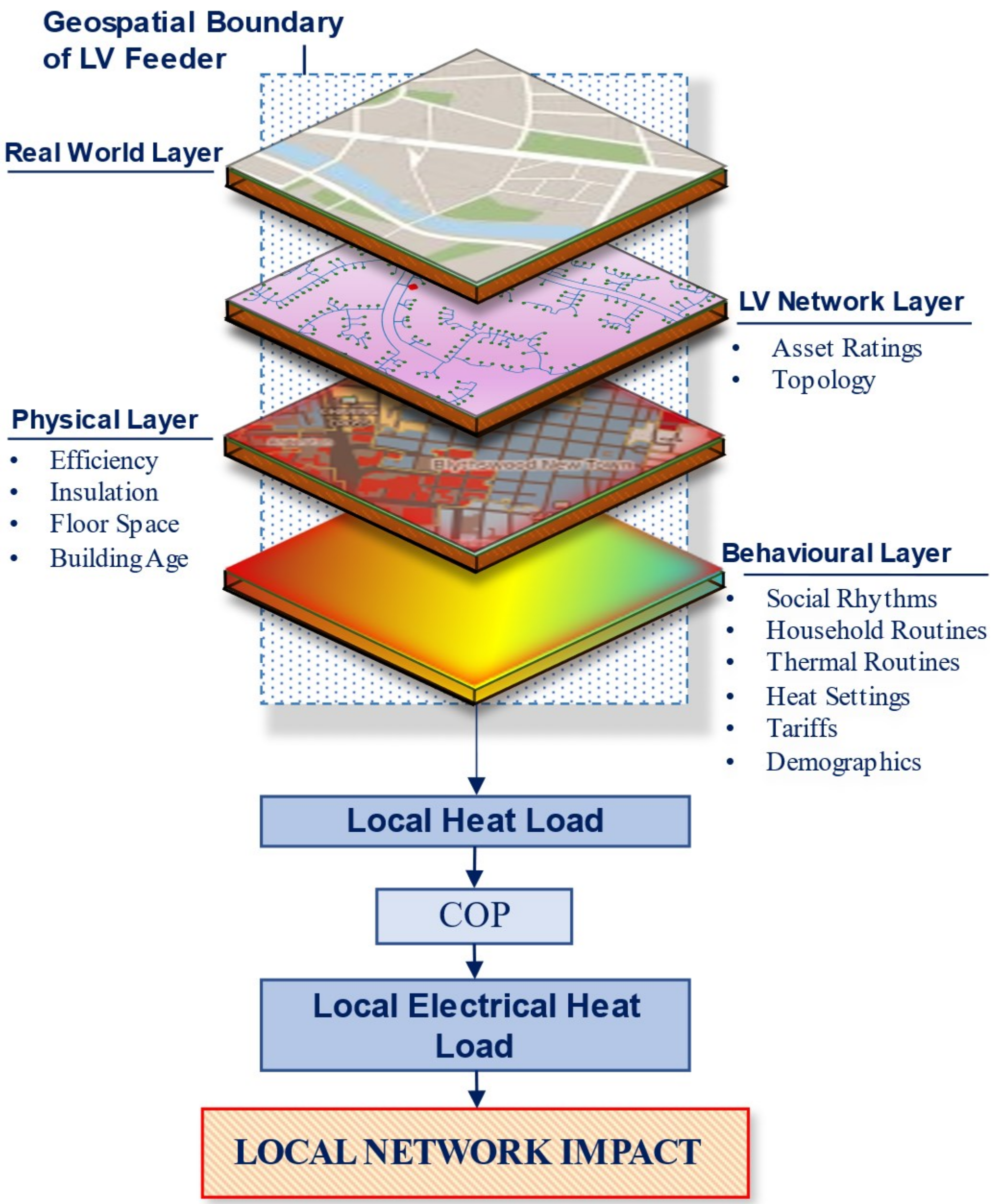


Figure 4-1 Basic relational structure between geographic boundary, geospatially linked physical and behavioural components, heat load and final electrical heat load imposed on the distribution network

In the last decade electric heat pumps (EHP) have transitioned from a fringe solution for low-carbon heat [148] to a key component of the UK government's strategy to decarbonize the domestic heating sector [27] [149]. Alongside this, the sophistication of heat pump load modelling techniques has progressed in recent years in step with the increasing relevance and maturity of the technology as well as the needs of the energy sector. The earliest efforts to assess heat pump network effects in the UK were constrained by a total absence of data, limiting assessments to user surveys to capture non-technical information [148] and small scale trials [150] [151]. Improvements in availability of load data through industry trials have facilitated the development of methodologies for modelling highly aggregated load on national scales, typically under winter-worst case conditions [76] [152]. Studies performed at the household-level modelled the relationship between detailed physical building parameters, occupant routines, heat pump activity and therefore heat pump electrical load [126].

However, modelling heat pump electrical load with the geospatial granularity appropriate for distribution networks imposes unique constraints not fully addressed by existing techniques. In addition to the ratings of the heat pump used, electrical heat demand is proportional to the physical characteristics of a building, such as construction type and insulation materials, as well as the behavioural routines of the occupant [114] and climatological conditions [153].

These parameters are subject to local variation due to different geospatial distributions of housing types [128], customer demographics and other influences such as levels of urbanisation; this geospatial variability has not been addressed by existing works which to date have focused on highly aggregated load profiles.

This chapter seeks to address the issue of electrical heat demand localisation by developing an approach for locally scaling electrical heat demand predictions from pre-existing annual gas meter data. Whilst this work draws on UK-specific datasets, this method demonstrates the use of supplementary data to leverage improved insights where distribution-network type impact studies are typically data constrained.

The contribution of this chapter is therefore as follows:

- To develop a heat demand scale localisation mode appropriate for distribution network analysis that can scale heat demand (and consequently electrical heat demand) sensitive to geospatially variable parameters such as building construction and demographics
- Coupling of the heat demand scaling model with the previously developed heat demand shape model [153] to provide an end-to-end conversion of annual gas demand to half hourly electrical heat demand suitable for LV network impact studies.
- To demonstrate the value of using localised heat demand predictions for LV network impact studies, as opposed to blanket application of pre-existing trial data. This is performed by a demonstration of After Diversity Maximum Demand (ADMD) versus local heat demand, and through a network case study that quantifies the impact of increasing HP penetration.

UK gas meter data is freely available at annual resolution down to the postcode level for all gas-connected households. 86% of UK properties use gas as the source for their primary heating system [154]. This translates into a potential data source with greater geographic granularity and breadth than existing heat pump trial data or parameter-based models, that can complement existing works and leverage future analysis as part of isolated heat pump effects analysis or as part of multi low-carbon technology (LCT) studies.

This chapter has been organised as follows. Section 4.2 documents the methodology developed in this work. Section 4.3 describes datasets used in the model development and application process in this work. 4.4 outlines the theoretical foundation for the conversion of annual gas demand to daily electrical demand in the presence of limited data, and demonstrates and tests the outlined methodology versus the training data, quantifying the error associated with this approach. Section 4.5 provides the developed conversion model, and Section 4.6 demonstrates application of the developed model in a network context performing an ADMD and network impact case study, deriving local heat demands and assessing the effects of increased heat pump penetration on real LV network feeders. Section 4.7 discusses the results of the methodology combined with the network impact assessment and identifies opportunities for future work.

4.2 Methodology Overview

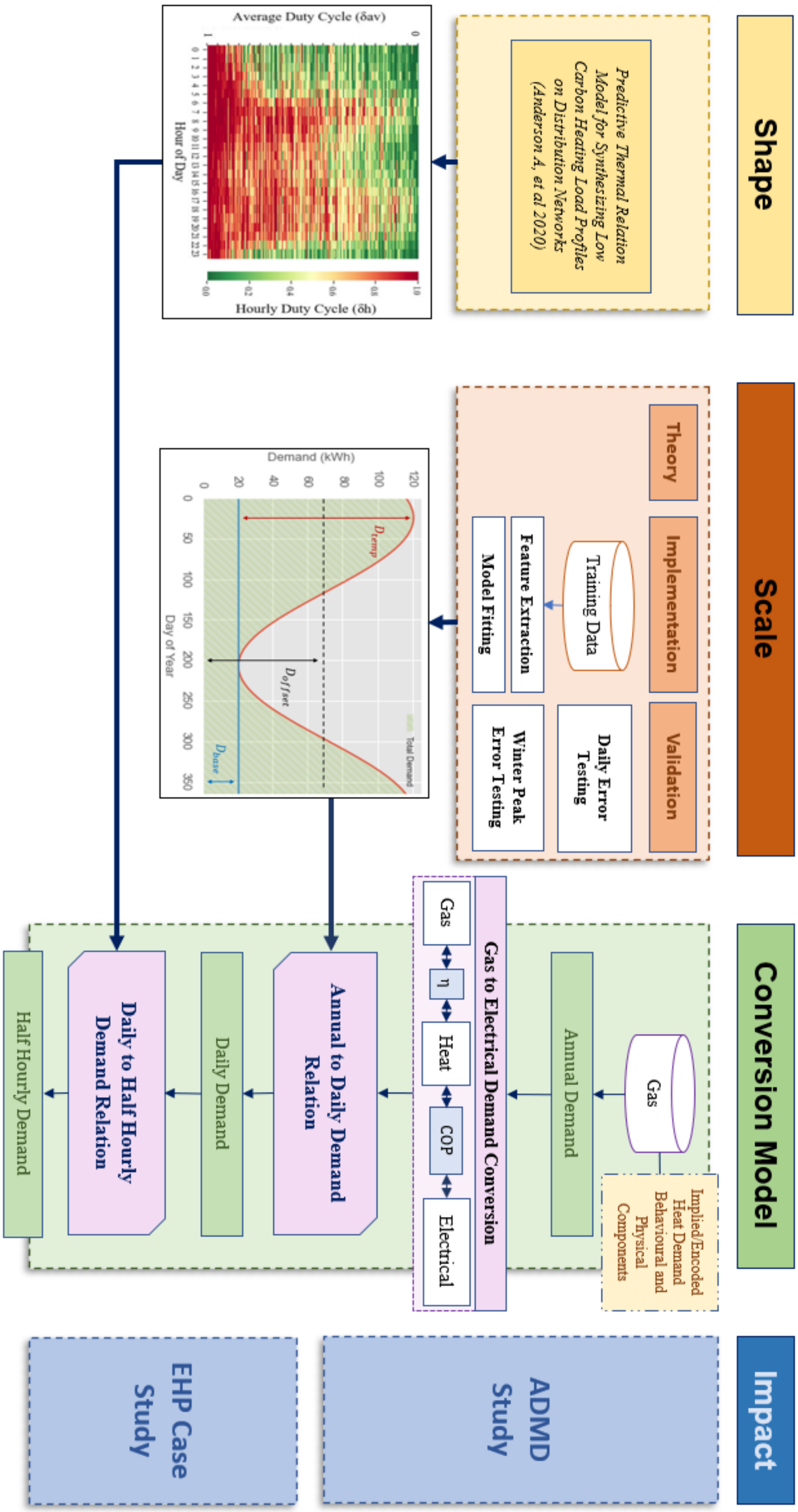


Figure 4-2 Detailed Methodology Overview for Scale Localisation of Electrical Heat

This work constructs a process for providing localised electrical heat load predictions, by drawing on previous electrical heat demand shape modelling work combined with a novel methodology for appropriately scaling the magnitude of electrical heat demand sensitive to local physical, behavioural and climatological parameters.

For electrical heat load, there are two primary components of interest:

- *load magnitude;* the scale of electrical heat load during active periods, proportional to the physical parameters of a household such as construction and insulation type.
- *load shape;* the time of day activity of the electrical heat load, linked to behavioural patterns of household occupants and thermal routines.

This work couples the load shape model developed in [153] with a novel methodology for determining the appropriate scaling for load magnitude through use of existing gas demand data. These components are then combined in a conversion model which performs the end-to-end translation of localised annual gas type demand into localised half hourly electrical heat demand suitable for LV network type studies. Figure 4-2 demonstrates the relationship between the existing demand shape model, combined with the novel scaling and end-to-end conversion model developed in this work. This conversion model is then used to quantify LV network impact for two case studies, demonstrating the sensitivity to the geospatial variability of electrical heat. A brief overview of each component is outlined below.

4.2.1 Heat Demand Scaling

In order to provide the magnitude localisation for heat demand shapes, this work draws on geospatially granular gas demand data to inform localised heat demand. Due to the annual resolution of this dataset, a model is developed to translate the data into predicted daily demand that can then be coupled to the load shape model.

This work exploits two fundamental theoretical relationships: the sinusoidal variation of seasonal temperature variation in high latitude environments, combined with direct proportionality of heating demand to daily average temperature [153]. By inferring that seasonal heat demand is directly proportional to the sinusoidally variable seasonal temperature, heat demand itself may be assumed to be primarily sinusoidal at a seasonal level. This sinusoidal characteristic is held to be applicable regardless of the specific heat demand type, but will naturally be subject to daily random variation due to temperature fluctuations and human activity such as public holidays and other routines. Furthermore, this proportionality will exist regardless of customer magnitude – a small household will have lower overall heat demand, but will still vary in a sinusoidally proportional manner to local temperature in the same way a large energy inefficient household would.

It is therefore hypothesized that each customer's seasonal demand variation can be represented as a sinusoid of fixed frequency and phase regardless of heat demand type or customer size, with each customer featuring their own unique amplitude and offset values that form the aggregate representation of the individual customers geospatially linked physical and behavioural parameters. Therefore, if the annual energy consumption (area under the sinusoid) is known, the unique amplitude and offset values for the customer can be inferred.

In order to define the sinusoidal function that approximates daily demand for each individual customer, the amplitude and offset parameters are extracted from the training demand datasets by linearizing the raw data and performing a simple linear regression. The output of this regression is to extract the unique amplitude and offset parameters that defines each customer's seasonal demand curve. These unique offset and amplitude values are then fitted to a generic probabilistic model that translates annual to daily demand with common fit parameters for all three heat demand types tested in this methodology; gas-type demand, electrical heat-type demand and direct-heat-type demand. This model is then validated versus the training datasets, with mean absolute percentage error (MAPE), mean absolute error (MAE) and Pearson's correlation coefficient (R) calculated versus the daily error and the peak error.

4.2.2 Heat Demand Shape

On half hourly timescales, electrical heat demand shape has been demonstrated to vary in accordance with the time of day, behavioural patterns, and occupancy routines of the user in addition to temperature [76]. Furthermore, it has been demonstrated that these load shapes are applicable regardless of the size of household being heated. This methodology uses load shape model developed in [153] in order to provide the time-of-day activity for the heat demand model; the load shape model probabilistically generates forty-eight half-hourly normalised load shapes sensitive to daily average temperature, daily total normalised demand, and level of customer aggregation. These normalised load shapes provide the base normalised electrical heat demand that is then scaled by the novel methodology developed in this paper.

4.2.3 Conversion Model

In order to transform the daily electrical heat demand into a series of sub-daily shapes, the electrical heat shape conversion model from [153] is applied combined with the electrical heat scaling methodology derived in this work. Through the use of linear thermal conversion efficiencies, gas demand is translated into heat demand, and then into equivalent electrical heat demand.

4.2.4 LV Network Impact

The developed model is then applied to the target temporal low-resolution, geospatially high-resolution dataset of interest, in this case the geographically granular BEIS (Department for Business, Energy & Industrial Strategy) Postcode Gas Demand dataset [155]. The derived model and global fit parameters are applied to the annual gas demand figure for the postcode or geographic area of interest, with daily electrical heat demand as an output.

Two case studies are performed to demonstrate this methodology in an LV networks context; an examination of localized ADMD versus number of customers and heat pump coefficient of performance (COP), and a network impact assessment performed on a real distribution network feeder. An average, high and low electrical heat demand case are examined in order to demonstrate the effects of localisation on average minimum endpoint voltage for a range of heat pump penetrations. Together these case studies demonstrate the utility of the developed model and allow localized comparisons to be made versus the averaged results in existing trial datasets.

4.3 Case Study Datasets

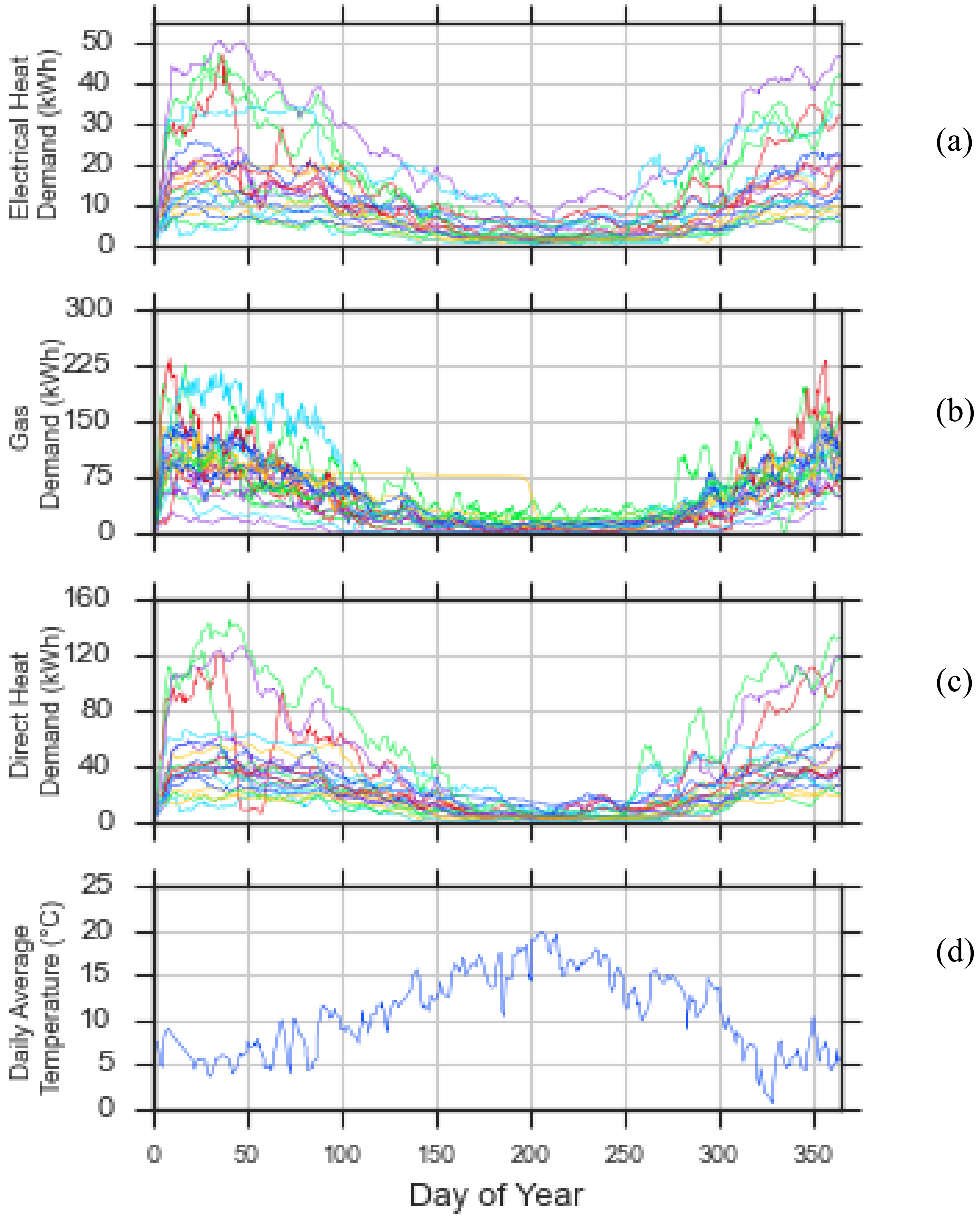


Figure 4-3 Plotting 30-day average demand for RHPP – Heat (a), RHPP – Electric (b) and Energy Demand Research Project (EDRP) - Gas (c) datasets for full duration of data capture.

Dataset	*EDRP [15]*	*RHPP [10]*	*RHPP [10]*	*Postcode BEIS [16]*
Heat Demand Type	Gas	Electric	Direct Heat	Gas
Model Function	Training	Training	Training	Target
Number of Customers/ Entities	4000	700	700	3 million
Sampling Frequency	30 minutes	2 minutes	2 minutes	Annual
Geographic Resolution	N/A	N/A	N/A	Average 15 households [156]
Date of Collection	2010	2012 - 2015	2012- 2015	2015 – Present

Table 4-1 Dataset overview for annual-daily winter peak demand translation

The datasets used within this study consist of the training datasets used to construct and test the relationship between annual and daily heat demand, alongside the target dataset where the daily heat demand will be predicted in the absence of data using the developed predictive model. Testing is performed versus the training dataset. Due to the legal obligation for sufficient anonymisation of data [157], there is generally a trade-off between the geographic granularity and temporal resolution of publicly available demand datasets. Generally, high temporal resolution demand data has been geographically anonymised or aggregated [115], whilst various government published datasets provide high geographic granularity with poor temporal resolution. Studies at the LV level necessitate access to data with high temporal and geographic resolution. This study uses three heat-type demand datasets with high temporal resolution that will be used to construct and test a model that then can be applied to the low temporal resolution, geographically granular dataset. These are tabulated in Table 4-1, showing the number of customers per dataset and sampling frequency versus heat demand type.

Samples of these three heat-type demand datasets are plotted in Figure 4-3, with conditioning of the raw demand data for clarity. For each heat-type demand (electrical heat (a), gas heat (b), and direct heat (c)), twenty random customers that have a full year of continuous demand data from each heat-type demand dataset are sampled. The 30-day rolling average for each customer is then plotted. For further context to demonstrate the seasonal variation of heat demand versus temperature, the daily average temperature [132] from the 2015 Central England dataset is plotted in (d).

4.3.1 Training Data

Three datasets are used to construct and test the relationship between annual and daily heating demand from existing heat-type demand data where both the annual and daily demand is known, such that the methodology may then be applied to low temporal resolution datasets where only the annual demand is known.

The first dataset; the Energy Demand Research Project (EDRP) dataset [158] consists of gas meter data collected in 2010 in order to provide improved insights into UK energy consumption at the time. Collected at 30-minute intervals with several thousands of customers, this dataset offers great breadth of individual behavioural variation but due to the anonymisation process there is no associated granular geographic information that can support correlation of metadata to directly measured demand. This forms the training gas demand dataset for this study.

Alongside this is the Renewable Heat Premium Payment (RHPP) dataset which consists of data collected from 700 [115] household heat pumps during the period 2013 – 2015 at a two minutely resolution. At the time this formed the largest European field trial of domestic heat pumps. Similar to the EDRP data, no associated geographic information is published with this dataset. The RHPP dataset forms the training electrical and direct heat demand datasets for this study.

4.3.2 Target Data

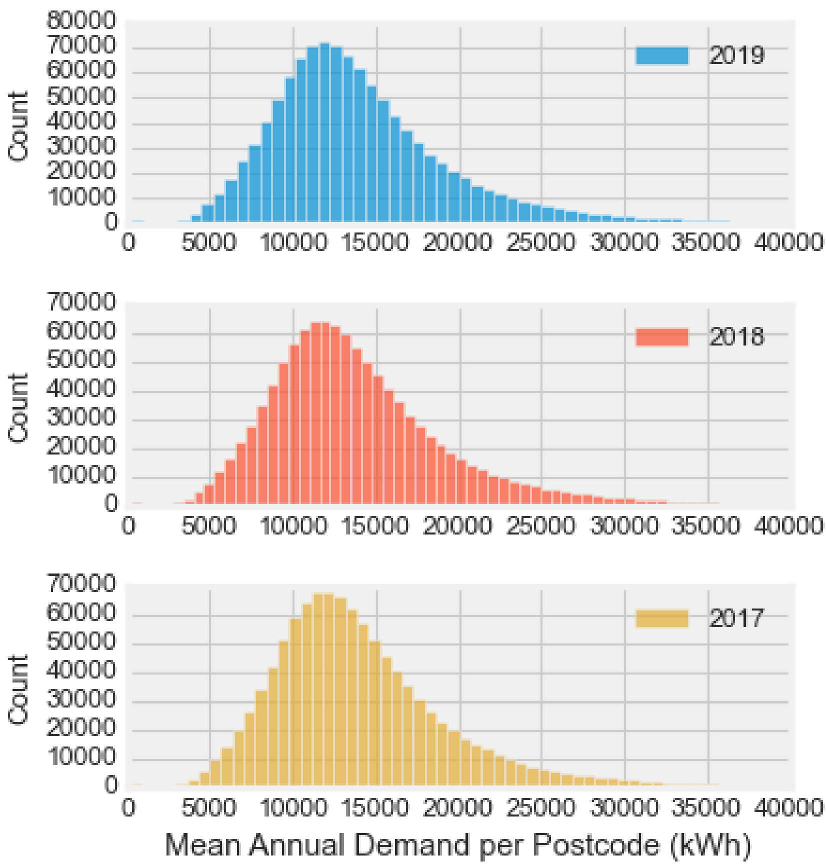


Figure 4-4- Distribution of Annual Gas Demand 2017, 2018 and 2019 per Postcode

The target dataset for this study is the BEIS Postcode Gas Demand dataset [155]. This features annual gas meter information for 1.1 million postcodes in the UK, with each postcode representing an average of 15 households. This dataset therefore features high spatial granularity but very low temporal resolution. This dataset has been released in annual editions every year since 2015 to the present day and therefore represents an up-to-date view of UK gas-provided heat demand. For this work the release from 2019 is used; 2020 was not used due to the exceptional circumstances caused by the outbreak of Covid-19 and the consequent disruption to normal heating routines and data collection. The inherent value of this dataset is therefore due to several complementary factors; in contrast to trial data [2] [115], the dataset is a contemporary representation of gas demand as opposed to being several years old, in addition to being geographically granular, geographically comprehensive and reflecting the demand characteristics of a mature heating technology. The postcodes provided in the dataset provide gas demand for 119 unique postcode area codes, and 2524 unique postcode district codes. Using the total known codes for each geographic level provided in [156], the coverage in the dataset constitutes of 95.9% of all postcode area codes, and 80.95% of all postcode district codes within the UK.

4.4 Scaling of Electrical Heat Demand

4.4.1 Theoretical Relationship between Annual and Daily Demand

This section will demonstrate the fundamental theoretical components between annual heat demand and daily heat demand that the core predictive model will be constructed with using the training heat demand type datasets. The key goal of this section is to demonstrate that an individual household's daily heat type demand is periodically proportional to annual total heat type demand, regardless of local climate, geography, behavioural factors or the specific heat demand type. This sinusoidal proportionality can then be exploited in order to derive a peak winter demand or intermediate daily demand from a single annual total demand figure.

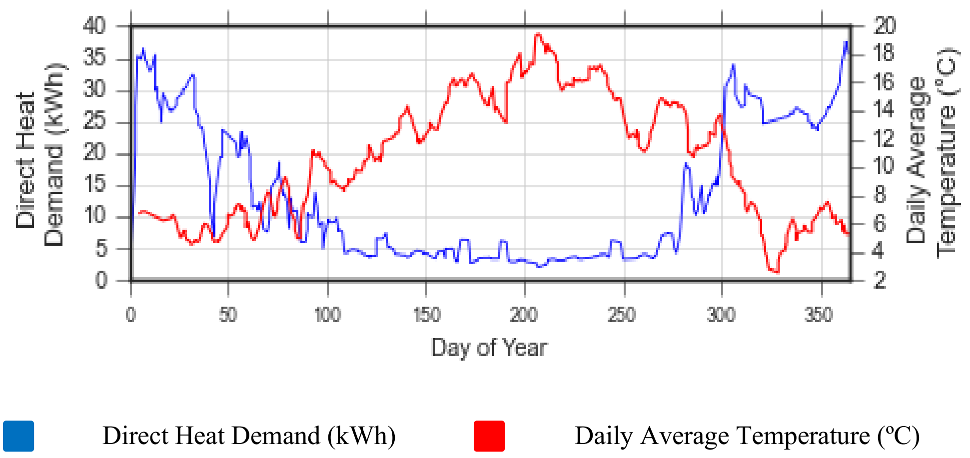


Figure 4-5 Demonstration of inverse relationship between seasonal mean daily temperature (°C) and seasonal mean daily demand (kWh) for single customer from direct heat training dataset.

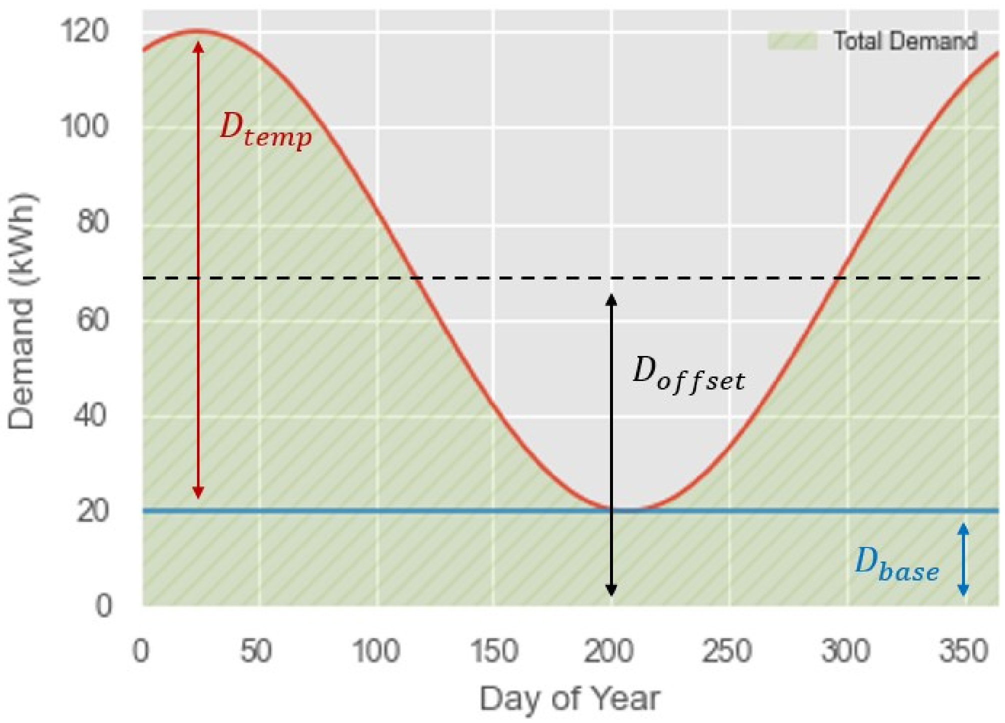


Figure 4-6 Theoretical demand composition illustrating temperature dependent (D_{temp}) and non-temperature dependent (D_{base}) components.

Heating demand for an occupied property is primarily linked to the ambient external air temperature, the desired internal temperature [3] and the physical parameters of the property that determine the input energy required to bring the building to a comfortable steady state condition for the occupant. Whilst the physical parameters and desired internal temperature remain more or less static on seasonal timescales [159] [160], the external air temperature varies seasonally in accordance with the local climate of the property. For non-equatorial locations this translates into large variation between the seasonal minimum and seasonal maximum demand and therefore an equivalent large variation on electrical network conditions. At a seasonal level, behavioural effects such as daily usage patterns are minimized and that on a daily or longer time scale demand is fundamentally proportional to temperature rather than behavioural components [76]. Due to the sinusoidal characteristic of seasonal temperature variation [161] mean daily heating demand can therefore be approximated as a fixed frequency sinusoid. This can be further deconstructed as follows, with the mathematical relationship shown in (23) and visually in Figure 4-6.

- D_{temp} determines the maximum magnitude of the temperature dependent demand component.
- D_{base} represents the positive offset from the x-axis and therefore the non-temperature dependent component of the overall demand.
- D_{offset} represents the total offset of the sinusoidal function.
- Frequency f is determined by the length of the year.
- Phase ϕ is constant and is used to offset the lag between the Gregorian calendar and seasonal temperature minimum and maximums.

$$f\ (D) = \frac{D_{temp}}{2}\sin(2\pi f + \phi) + D_{offset} \tag{23}$$

$$D_{base} = D_{temp} - D_{offset} \tag{24}$$

$$D_{temp} \geq D_{base} \tag{25}$$

$$D_{max} = D_{temp} + D_{base} \tag{26}$$

This definition allows the idealized sinusoid to be decomposed into the temperature dependent and non-temperature dependent components. By assuming the function as a sinusoid plus fixed offset D_{offset} , overall demand may therefore be represented as a fixed non-temperature dependent load plus varying temperature dependent sinusoid. This is key as while household gas demand in the UK is primarily heating, non-temperature dependent components such as cooking and water heating contribute a continuous seasonal load that is largely insensitive to temperature and minimal in scale to peak heating demand [162]. Additionally, due to local climate or personal preference, some households may maintain a heating baseload throughout the year [114]. Assuming that the temperature dependent component is the most significant portion of the overall gas demand and that the overall demand function closely approximates an ideal sinusoid, it is therefore possible to model the daily demand using the annual consumption as a single input. For a pure sine wave, the area under the curve is proportional to the maximum amplitude. In this case the area under the curve represents the total annual gas consumption D_{annual} for a particular customer, which is then related to the maximum demand D_{temp}.

$$D_{annual} = \int_0^{2\pi} \frac{D_{temp}}{2} \sin(2\pi f + \phi) + D_{offset} \tag{27}$$

This may then be used to extrapolate the daily winter demand peak that will be experienced at the minimum seasonal temperature as well as intermediate daily demand figures throughout the year. This relationship will be used to derive a predicted daily winter peak demand from a measured annual demand, supporting network analysis on seasonal and daily timescales in the presence of low temporal resolution demand data.

4.4.2 Application of Sinusoidal Approximation to Demand Datasets

This section outlines the process used to extract the customer specific sinusoidal amplitude and offset fit parameters from raw heat-type demand data. Beyond this the sinusoidal parameters are used to fit the training datasets such that predictions can be made for the target dataset using a single unified model that is insensitive to heat demand type.

The methodology can broadly be split into initial conditioning of the data, parameter extraction and dataset fitting.

4.4.2.1 Data Conditioning

A common process was applied to all three training datasets in order to cleanse, condition and format the data prior to forming the annual to winter peak demand model. Users from the RHPP and EDRP datasets with less than 12-month continuous demand data were discarded and the time period was resampled from 2-minutely to daily for the RHPP dataset and from 30-minutely to daily for the EDRP dataset. Customers with periods of zero data were intentionally retained as this could reflect household absence rather than communications errors.

4.4.2.2 Parameter Extraction

As has been described previously, daily heat demand may be represented as a sinusoidal function at a seasonal level due to its proportionality with seasonal temperature variation. Each customer therefore features a unique amplitude and offset value that reflects demand magnitude and ratio of temperature dependent to non-temperature dependent load. These unique amplitude and offset values are extracted from the conditioned training datasets through application of a univariate linear regression. (28) is used to convert the x-axis in the original time series data for each customer from day of the year to day angle, where day of year ranges from 1 to 365 and day angle ranges from -1° to 1°. This folds the sinusoidal function into a linear function as shown in Figure 4-7, allowing representation in the generalised linear form provided in (30). In the linear form β_0 forms the y-intercept and is equivalent to D_{base} in the sinusoidal form (24) (31). β_1 forms the gradient of the linear regression and is equivalent to D_{max} in the sinusoidal form (26) (32). ε represents the general error function of the solution.

The output of this process is to derive from the raw demand data for gas, electrical and heating types, the unique set of β_0 and β_1 values for each customer that can then be related to the annual demand figure. Using the fully visible training dataset the relationship between real annual and real peak demand is examined alongside the predicted peak demand; this process is performed in the next section.

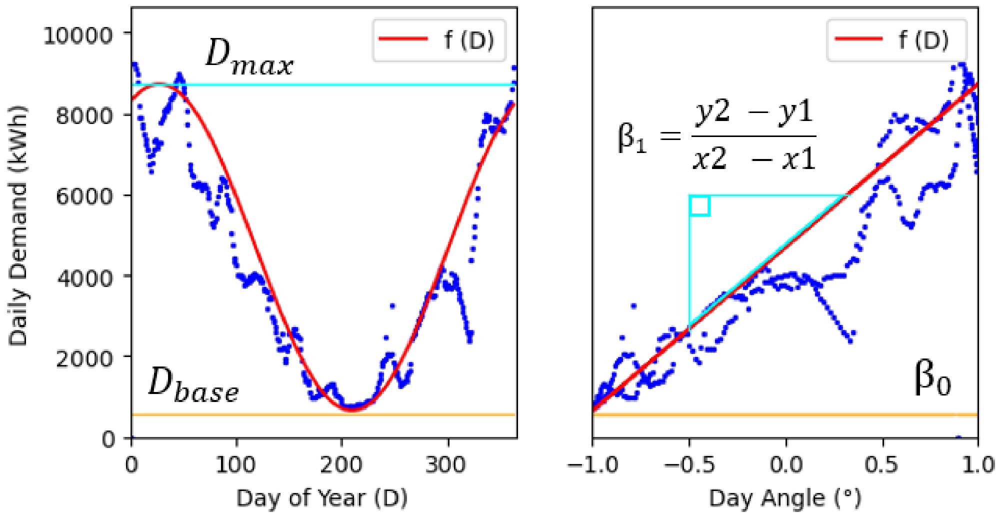


Figure 4-7 Transformation of Sinusoidal Function (left) to Linear Form and Linear Regression (right) for example customer

$$f\ (°) = \sin(\frac{Day\ of\ Year}{365}\ 2\pi + \phi) \tag{28}$$

$$\phi = \ 1.1 \tag{29}$$

$$f\ (D) = \ \beta_0 + \beta_1 \times f\ (°) + \varepsilon \tag{30}$$

$$\beta_0 = \ D_{base} \tag{31}$$

$$\beta_1 = \ D_{max} \tag{32}$$

Table 4-2– Sinusoidal and Linear Forms for Daily Demand

Parameter	Sinusoidal Form	Linear Form

Total Daily Demand	$f\ (D) = \frac{D_{temp}}{2}\sin(2\pi f + \phi)$ $+(D_{temp} - D_{base})$	$\beta_0 + \beta_1 \times f\ (^\circ)$
Temperature Dependent Component	$\frac{D_{temp}}{2}\sin(2\pi f + \phi)$	$\beta_1 \times\ f\ (^\circ)$
Non-Temperature Dependent Component	D_{base}	β_0

4.4.2.3 Dataset Fitting

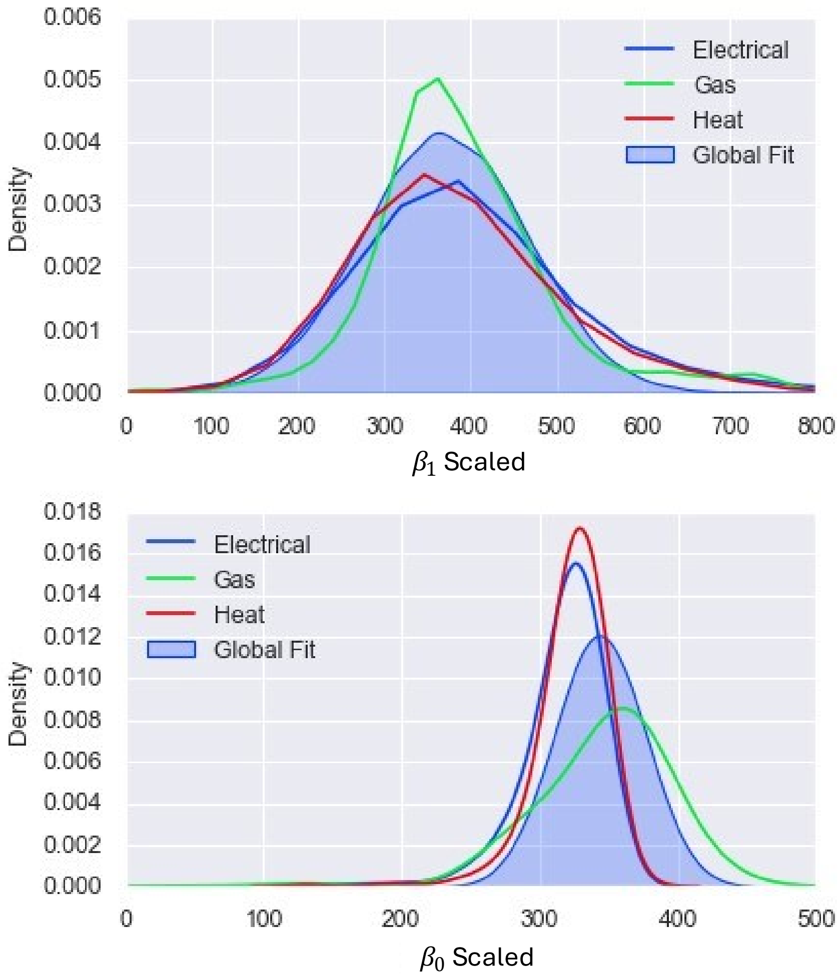


Figure 4-8 β_{1_Scaled} distribution (top) and β_{0_Scaled} distribution (bottom).

This section outlines the methodology for translating the individual customer sets of β_0 and β_1 values extracted in the previous section from the gas, electric and direct heat training datasets into representative probability distributions that will reflect the fitted amplitude and offset values extracted for each of the demand datasets. This relies on two basic assumptions that will be tested:

- Heat demand is fundamentally sinusoidal regardless of heating technology type.
- Therefore, an individual customers amplitude and offset are intrinsically proportional to the same individual's total annual demand, regardless of customer size.

For all customers in the heat, gas and electrical training datasets an β_1 (amplitude) and β_0 (offset) value have been derived through the previously described parameter extraction section. In order to transform all customer values to a common scale, the unique β_0 and β_1 values for each customer are normalized with respect to each individual customers unique annual demand, as illustrated in (33) and (34).

$$\beta_{0\_Scaled} = \frac{D_{Annual}^{Kwh}}{\beta_0} \tag{33}$$

$$\beta_{1\_Scaled} = \frac{D_{Annual}^{Kwh}}{\beta_1} \tag{34}$$

The probability distributions of the normalized β_{0_Scaled} (33) and β_{1_Scaled} (34) values for the training datasets are illustrated in Figure 4-8. As per Table 4-2, β_0 reflects the offset or non-temperature dependent component of the load profile. β_1 represents the amplitude, or temperature dependent component of the load profile that varies seasonally. The three probability distributions derived from the heat-type demand datasets are then averaged [163] in order to construct global probability distributions for β_{0_Scaled} and β_{1_Scaled} as per (35) and (36), which are also plotted in Figure 4-8. A normal distribution will be used in order to provide a general fit.

Two primary observations can be made. The β_{1_Scaled} distribution for all datasets features a very closely aligned mean; 387 for gas, 394 for electric and 391 for heat. This confirms that the amplitude (m) for all heating types is fundamentally proportional to annual demand through the sinusoidal assumption. Furthermore, this illustrates that even for real demand data this sinusoidal characteristic remains dominant. The offset of the $P(\beta_{0\_scaled}^{gas})$ distribution with respect to the $P(\beta_{0\_scaled}^{electrical})$ and $P(\beta_{0\_scaled}^{direct\ heat})$ illustrates that, on average, gas type demand features a higher slightly 0 offset value than electrical and direct heat type demands. This is to be expected due to gas type demand incorporating non-heat type functions such as cooking [164] and therefore contributing a higher baseload.

$$P\left(\beta_{0\_\mathrm{scaled}}^{global}\right) = \frac{P\left(\beta_{0\_\mathrm{scaled}}^{electrical}\right) + P\left(\beta_{0\_\mathrm{scaled}}^{gas}\right) + \left(\beta_{0\_\mathrm{scaled}}^{direct\ heat}\right)}{3} \quad (35)$$

$$P\left(\beta_{1\_\mathrm{scaled}}^{global}\right) = \frac{P\left(\beta_{1\_\mathrm{scaled}}^{electrical}\right) + P\left(\beta_{1\_\mathrm{scaled}}^{gas}\right) + \left(\beta_{1\_\mathrm{scaled}}^{direct\ heat}\right)}{3} \quad (36)$$

$$P\left(\beta_{\mathrm{n\_scaled}}^{global}\right) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad (37)$$

4.4.3 Model Validation

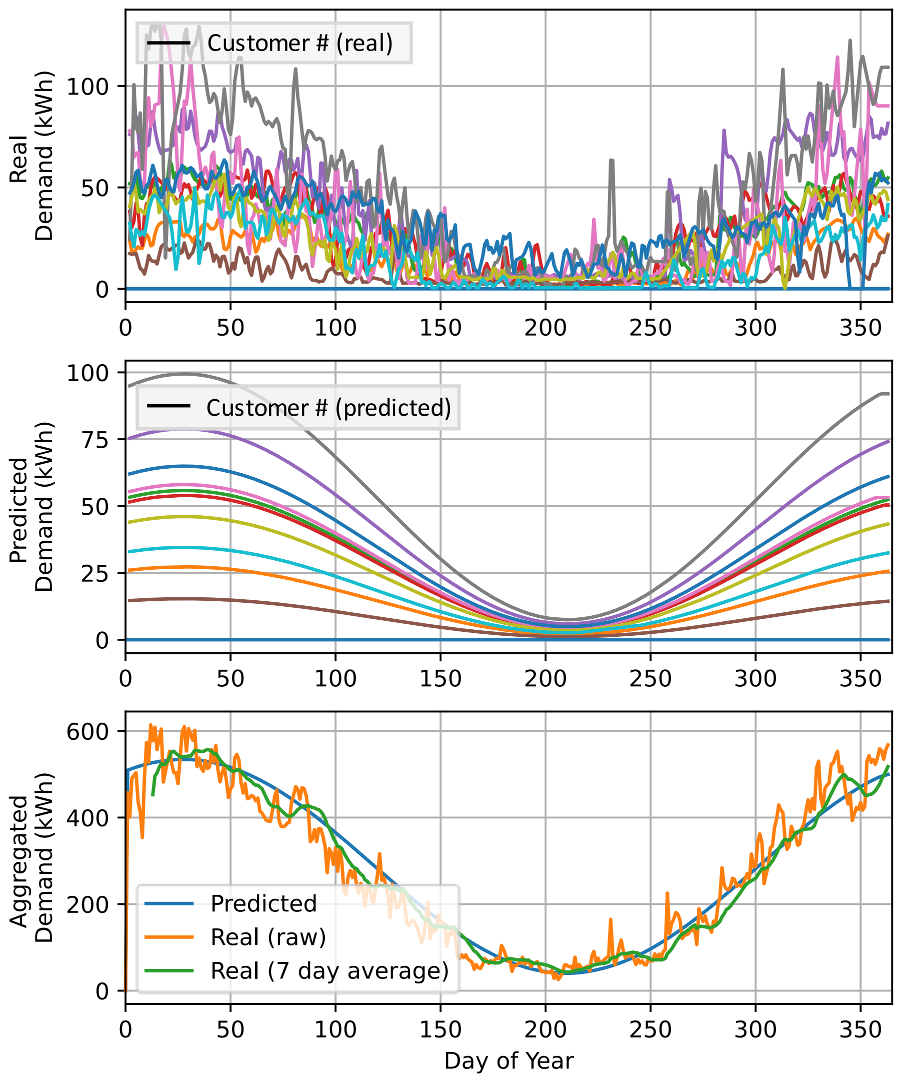


Figure 4-9 Real raw demand profiles (top) versus synthetically generated demand profiles (middle), and aggregated real versus predicted demand (bottom)

Modifying the generalized linear form presented initially in (10), the daily demand for any day of the year for any heat type demand can now be predicted using only the known annual demand D^{kWh}_{Annual} and the global probability distributions $P({\beta_0}^{scaled}_{global})$ and $P({\beta_1}^{scaled}_{global})$ constructed in pervious sections. This output is presented in (38) and demonstrated visually in Figure 12 for customer sets of varying population sizes.

$$f\ (D_{pred}) = \frac{D_{Annual}^{kWh}}{P(\beta_{0\,global}^{\ scaled})} + \frac{D_{Annual}^{kWh}}{P(\beta_{1\,global}^{\ scaled})} \times f\ (°) \tag{38}$$

Two general tests are performed to assess the quality of the model output and assess the sensitivity of this methodology to heat demand type:

- Daily Error testing: Calculation of MAPE and coefficient of determination for general daily error case.
- Winter Peak Error testing: Calculation of MPE for Daily Winter Peak demand.

General daily error is of interest to assess the quality of the predictive model for applications where continuous time series load profiles are applied, such as in studies incorporating multiple low carbon technologies. Peak error is of interest as this is an indication of the worst-case network conditions, and in itself influences ADMD which is an established metric for LV network planning [89].

Figure 4-10 illustrates the workflow for computing the model error. The developed model will be tested versus populations of customers to assess the error at a typical LV network scale. For each heat demand type, random customers are selected from the global training dataset pool to generate customer group sizes of 1, 5, 10, 25, 50, 75 and 100. For each customer group size 100 random samplings are performed, with the error for each sampling being calculated and averaged.

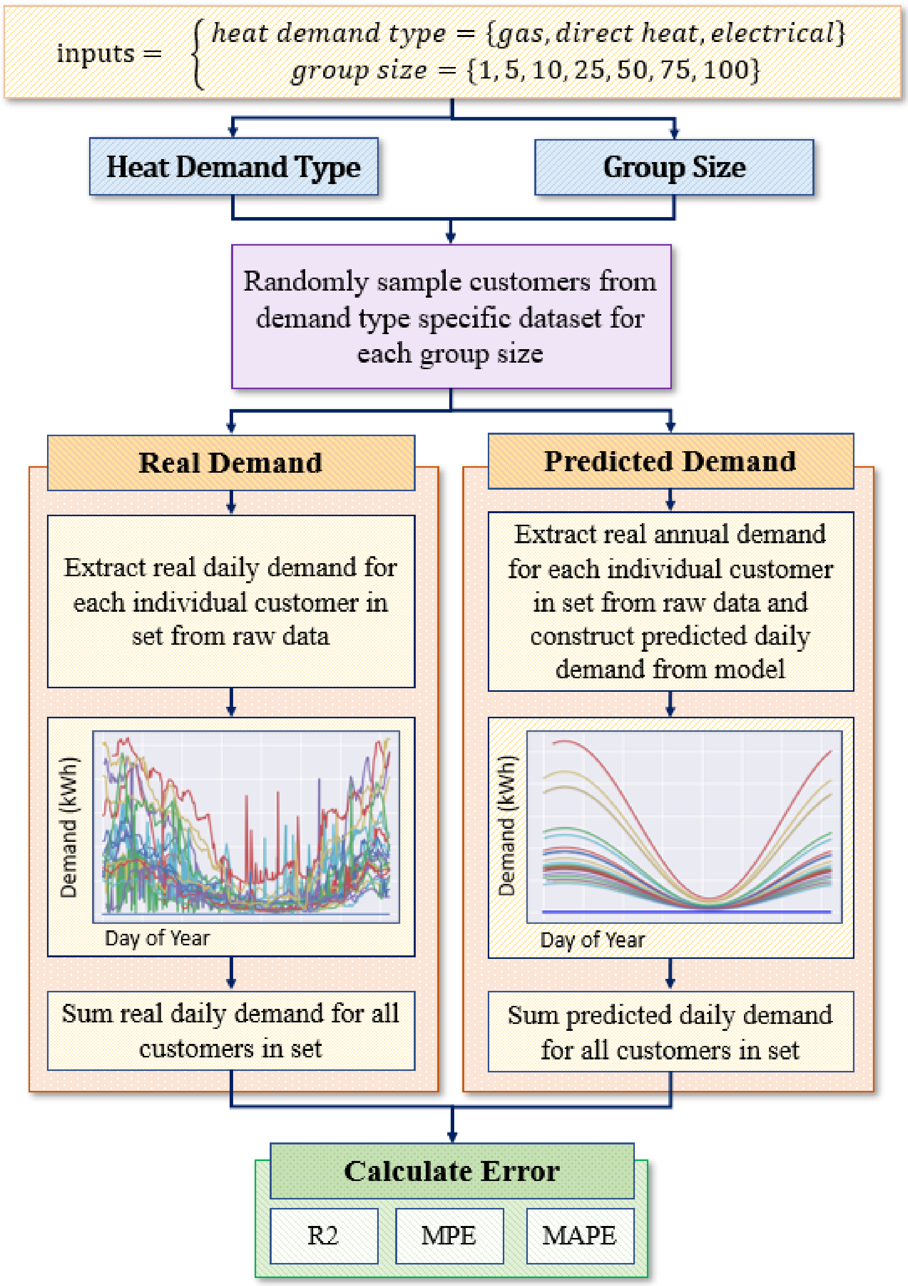


Figure 4-10 Workflow for predicting peak daily demand from annual demand and validation

4.4.3.1 Daily Error Testing

The $f\ (D_{pred})$ function for a continuous 365-day period is computed for each individual customer in a customer set and the daily mean absolute percentage error and coefficient of determination R^2 (39) with respect to the measured values are calculated. For all heat demand types, the R^2 converges on greater than 0.95 for customer group sizes of 25 or above. Similarly, the MAPE converges on less than 10% for all heat demand types for customer group sizes of 25 or greater.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \tag{39}$$

$$MAPE\ (\%) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{f\ (D_{real}) - f\ (D_{pred})}{f\ (D_{pred})}\right| \tag{40}$$

4.4.3.2 Winter Peak Error Testing

The sum total of the predicted winter peak versus the real winter peak for each group is calculated as per (21), where the value of $f\ (°)$ is set to the maximum day-angle of 1° to obtain the annual peak. Mean percentage error is calculated as per (42).

$$D_{daily} = \left(\frac{D_{annual}^{kWh}}{P({\beta_0}_{global}^{scaled})} + \frac{D_{annual}^{kWh}}{P({\beta_1}_{global}^{scaled})}\right) \times 1 \tag{41}$$

$$MPE\ (\%) = \frac{100\%}{n}\sum_{i=1}^{n}\frac{D_{real} - D_{pred}}{D_{real}} \tag{42}$$

Figure 4-11 shows the mean percentage error and standard deviation for each of the group size and heat demand type combinations. This illustrates that for all three heating types the error converges on a low mean percentage after approximately 25 customers, despite the inherent offset associated with each case. For distribution network forecasting applications, errors of 11% to 16% have been achieved elsewhere [137].

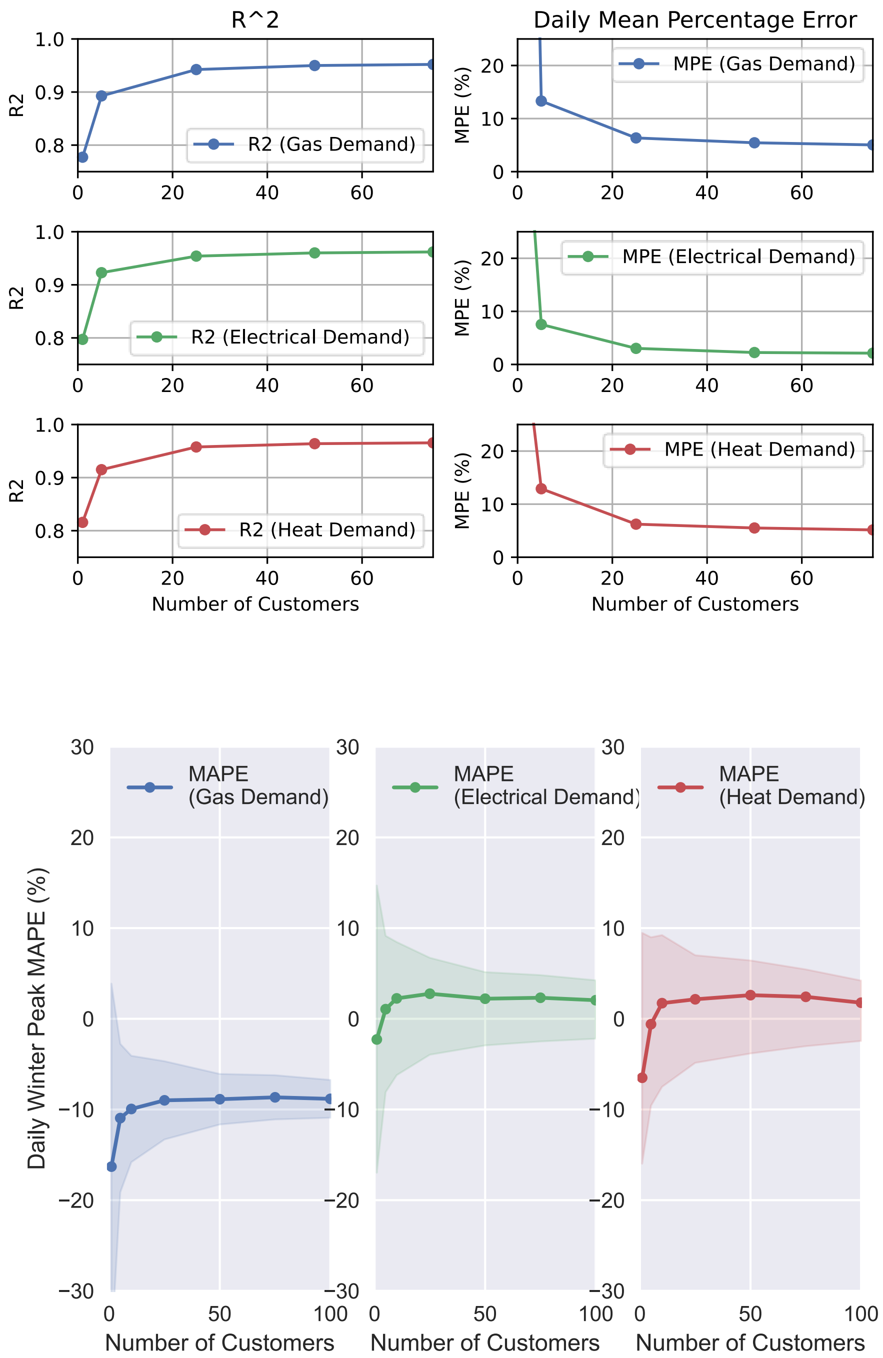


Figure 4-11 R^2, Daily Mean Percentage Error and Daily Winter Peak MAPE for Model

4.5 Conversion Model

Figure 4-12 Gas, Direct Heat and Electrical heat type demands and their associated conversion factors η (gas to heat conversion efficiency) and COP (coefficient of performance, heat to electrical heat conversion efficiency)

This section outlines the process for transforming input annual gas demand into half hourly electrical heat demand using the annual to daily demand relation developed in this work and the daily to half hourly demand relation developed in [153]. The conversion model provides the link between a geographic area, input gas demand and the translation into a half hourly electrical heat demand suitable for LV network impact analysis.

The workflow for this process is shown visually in Figure 4-13. Beginning with the input annual gas demand D_G^{annual}, this is converted into the peak winter value D_{pred} as per (41). The input n represents the number of customers that corresponding D_{pred} values are generated for. Gas, direct heat, and electrical heat type demands are all expressions of the input energy required to bring a household to a target temperature level. Using appropriate conversion efficiencies, translation between heat type demands can be performed as shown in Figure 4-12. To translate daily gas demand into the equivalent electrical demand, two conversion efficiencies must be considered. The first η accounts for the gas to heat efficiency of the gas boiler system, typically 80% to 90%. [103]. More recently, the Boiler Plus Standards introduced in England in 2018 mandate a minimum efficiency standard of 92%, but this is only applicable to new installations [165]. For this study a single gas-to-heat efficiency of 85% is used in order to approximate average boiler efficiency rather than specifically modelling older or newer boiler efficiencies. Therefore, in order to transform the predicted direct heat demand from gas the equation in (43) is applied. The second efficiency COP (coefficient of performance) represents the efficiency of the electrical to heat conversion for the heat pump system, typically 2.5 to 3 for modern systems [28]. This is applied as shown in (24) in order to derive the equivalent daily electrical heat daily demand D_E^{daily}.

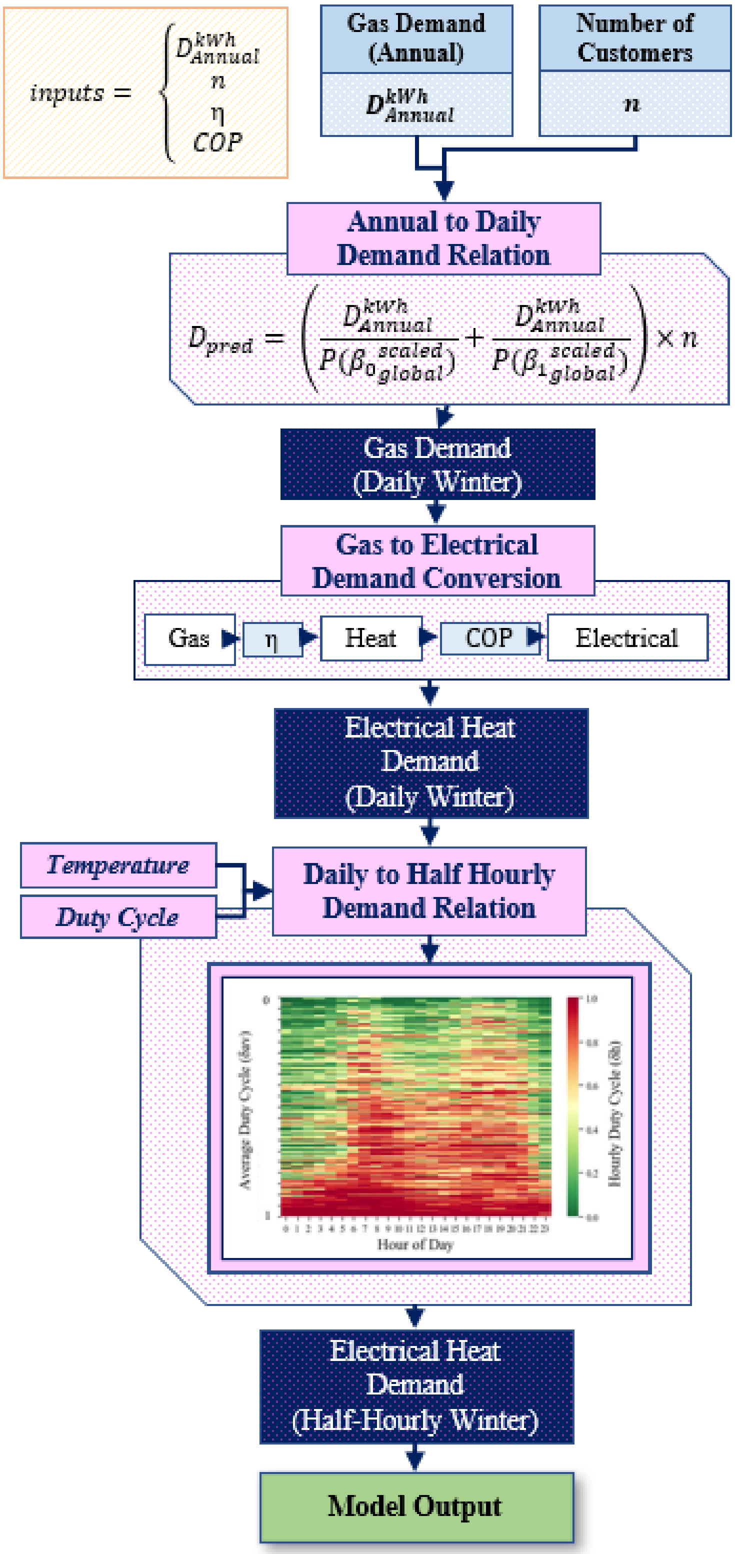


Figure 4-13 Workflow for conversion of Annual Gas Demand to Half Hourly Electrical Heat Demand

Each of the application case studies uses a common process for transforming D_G^{annual} into equivalent half-hourly electrical heat demand D_E^{hh} load profiles suitable for localized distribution network analysis.

The workflow for this process is shown visually in Figure 4-13. Beginning with the input annual gas demand D_G^{annual}, this is converted into the peak winter value D_{pred} as per (41). The input n represents the number of customers that corresponding D_{pred} values are generated for. Gas, direct heat and electrical heat type demands are all expressions of the input energy required to bring a household to a target temperature level. Using appropriate conversion efficiencies, translation between heat type demands can be performed as shown in Figure 4-13. To translate daily gas demand into the equivalent electrical demand, two conversion efficiencies must be considered. The first η accounts for the gas to heat efficiency of the gas boiler system, typically 80% to 90%. [103]. Therefore, in order to transform the predicted direct heat demand from gas the equation in (23) is applied. The second efficiency COP (coefficient of performance) represents the efficiency of the heat to electrical conversion for the heat pump system, typically 2.5 to 3 for modern systems [102]. This is applied as shown in (24) in order to derive the equivalent daily electrical heat daily demand D_E^{daily}.

$$D_H^{daily} = \frac{D_G^{daily}}{\eta} \qquad (43)$$

$$D_E^{daily} = \frac{D_H^{daily}}{COP} \qquad (44)$$

In order to perform the final transformation between daily electrical heat demand D_E^{daily} the probabilistic electrical heat load shape model from [153] is used in order to relate the input daily demand magnitude D_E^{daily} to a set of 48 half hourly demand magnitudes. An input temperature of 0°C and the input duty cycle function derived from the RHPP dataset from [153] was used.

4.6 LV Network Impact

Having derived the methodology for transforming input annual heat type demand into half hourly electrical heat type demand, this section demonstrates the application of the derived approach in an LV network context through the following case studies:

- ADMD versus input annual gas demand and COP; estimating localized ADMD contributed by electrical heat load for a range of COPs
- LV network impact assessment versus increased electrical heat pump penetration.

ADMD remains a useful metric for DNOs in order to assess and size the physical ratings of network assets with respect to the maximum expected load conditions [89]. High penetrations of heat pumps stands to significantly alter existing design assumptions and it is therefore of interest to estimate locally specific ADMD from localised electrical heat load. Through these case studies the utility of the localized heat demand model will be demonstrated with respect to specific LV network impact assessment.

4.6.1 ADMD Study

This section will examine the variation in predicted ADMD due to electrical heat load, given the normal variation in annual gas demand in the BEIS dataset. ADMD is calculated as per the equation below (45), with the input variables listed in (46). n defines the number of customers, η is the gas-to-heat conversion efficiency, and COP is the heat-to-electrical heat conversion efficiency.

$$ADMD = \frac{1}{n}\sum_{i=1}^{N} P_i \tag{45}$$

$$inputs_{ADMD} = \begin{cases} D^{kWh}_{Annual} = \{-\sigma, mean, +\sigma \\ n = \{1, 5, 10, 25, 50, 75, 100\} \\ \eta = \{0.85\} \\ COP = \{2, 2.5, 3\} \end{cases} \tag{46}$$

Using the previously developed electrical heat shape model in chapter 3 [153], and the localized gas to daily electrical demand model derived in this work, a localized ADMD model can be constructed in order to predict a local ADMD contributed by electrified heating, sensitive to local building parameters and demographics. The mean, plus and minus one standard deviation with respect to the mean annual gas demands from the 2019 BEIS dataset are used as inputs for this study, whilst model inputs η, *COP* and number of customers *n* are varied in order to demonstrate the variation of ADMD with respect to number of customers, and heat conversion efficiency. Figure 4-14 demonstrates the output of this workflow. The sensitivity of final ADMD with respect to COP is clear; due to improvements in technology COPs have been improving in recent years [102]. The lower the number of customers and COP the more severe the potential network impact.

Figure 4-15 demonstrates the relationship between COP, ADMD and the variation with respect to the annual gas demand dataset. A one-standard deviation from mean input annual gas demand translates into approximately a 20% deviation in terms of predicted ADMD. This highlights that households that fall in postcodes with extremely low or high gas demands may be expected to have correspondingly low or high electrical heat load. Elsewhere, the ADMD curve obtained from the raw RHPP dataset in [76] falls between the mean case for a COP of 2 to 2.5. This suggests that the RHPP household sample set is broadly representative of the average housing stock of the UK reflected in the BEIS annual gas postcode dataset. Similarly, in the CLNR study, the ADMD of electrical heat pumps converged on 1.5kW for customer populations of 50 or greater [89]. For both the RHPP and CLNR studies, the advancements in typical HP COP with respect to when the trial data was originally collected will result in a shift in final estimated ADMD with respect to the original trial data. This work offers the capability to localize ADMD beyond the previously existing average representations into predictions sensitive to local parameters as well as the continual improvements in COP.

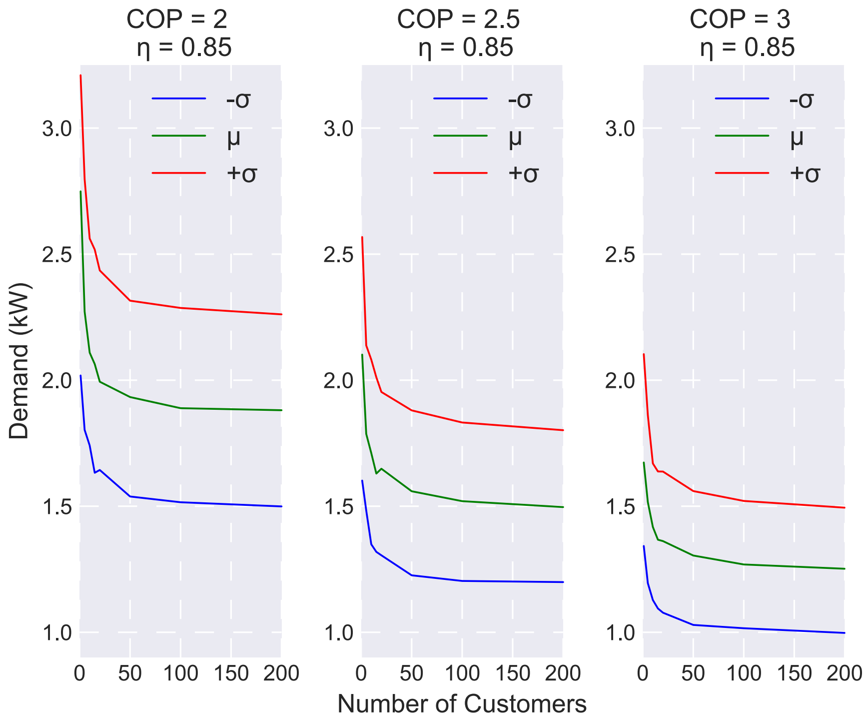


Figure 4-14 Localized ADMD (kW) for RHPP dataset

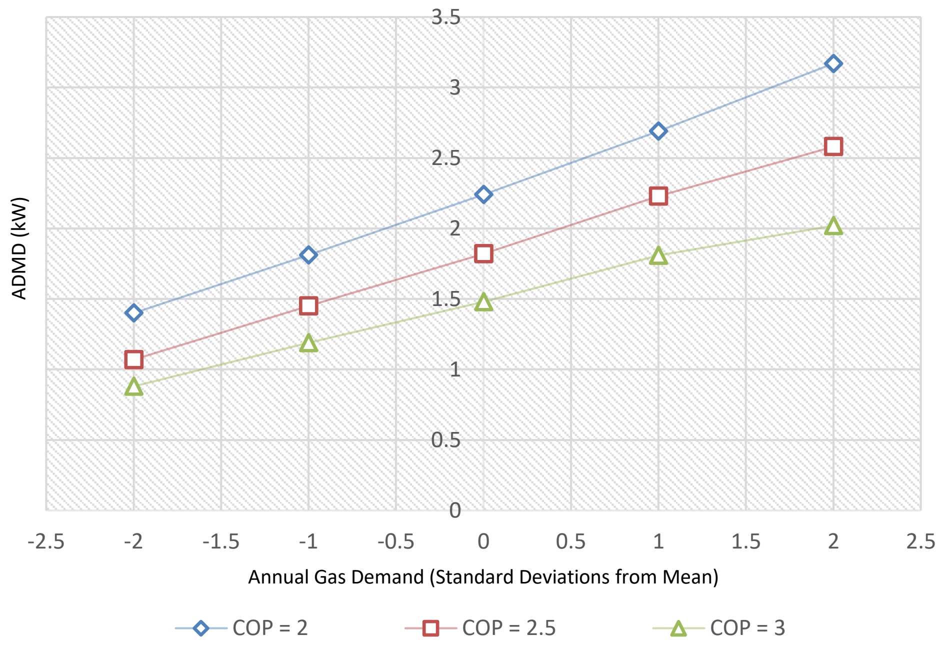


Figure 4-15 Variation in modelled ADMD versus variation in input Annual Gas Demand with respect to population mean.

4.6.2 LV Network Impact versus Increased Heat Pump Penetration

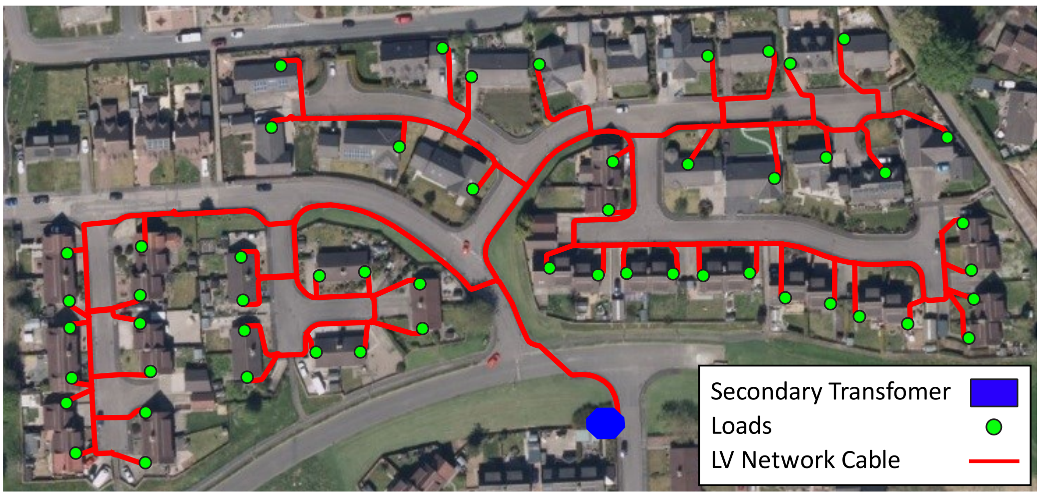


Figure 4-16 Aerial geospatial image of modelled feeder

To demonstrate the local heat demand methodology derived in this paper in a general network impact context, the approach is applied a real network 415V feeder. A low and high feasible postcode heat demand are taken from the 2019 distribution shown in Figure 4-4, converted into equivalent electrical demand through the workflow in Figure 4-13, and applied to the corresponding feeder, examining the potential impact of increased HP penetration. The impact of these demands is contrasted versus the electrical demand figure from the pre-existing RHPP dataset. Alongside this, the equivalent population average heat demand from the RHPP dataset is used.

The feeder is modelled in OpenDSS from GIS network data made available by SSEN (1 of 6 DNOs in GB). The feeder consists of 54 loads connected with an unbalanced phase distribution and has a total length of approximately 1600 metres; note that impedance and maximum current data for the cabling was matched to GIS cable type information based on [166] [167] [168]. An aerial geospatial image of the modelled feeder is provided in Figure 4-16 where Bing Aerial [169] and QGIS [170] are used for visualisation.

4.6.2.1 Network Impact Assessment Methodology

A 48 half-hourly daily Monte-Carlo style approach is taken to model the impact of increasing load growth due to HP uptake on the developed feeder for each postcode demand, where Exelon's demand profile for a winter's day [171] is used for the base load to represent a 'worst' case scenario. HP penetrations are then increased from 0% to 100% in 10% increments. The model developed in [153] is used to generate the daily behavioural profiles. For each penetration, HP loads are randomly distributed across the feeder loads and results are stored for a number of profiles and load locations per penetration. The minimum feeder endpoint voltage is used as a metric to quantify the operational consequence of the results. Therefore for each penetration step, the minimum feeder endpoint voltage represents the minimum voltage obtained across multiple random allocations of profiles and load locations.

4.6.2.2 Results

Figure 4-17 presents the results of the Monte-Carlo style impact assessment. A three-dimensional plot that shows average minimum feeder endpoint voltage for across the sample vs time vs HP penetration is presented where Figure 21(a)-(c) represents each individual postcode annual gas demand; 9000 kWh (low), 14,000 kWh (RHPP-mean) and 19,000 kWh (high) respectively. In comparison of Figure 21(a) and Figure 21(b) the low postcode demand scenario yields a higher average minimum endpoint voltage across the day as HP penetrations increase than compared with the RHPP-mean. This indicates that the impact from HP uptake is less severe, particularly in relation to the impact from the early morning space heating demand which sees the minimum endpoint voltage drop below 216 V at around 50% penetration in the RHPP-mean scenario compared with at 80% in the low scenario. The impact on the traditional evening peak is also reduced. In contrast, in comparison of Figure 4-17 (b) and Figure 4-17 (c), the impact of HP uptake on the minimum endpoint voltage is evidently more severe as a lower average minimum endpoint voltage across the day as HP penetrations increase is evident than compared with the RHPP-mean. The number of minimum voltage violations for the three 100% penetration scenarios are demonstrated in Table 4-3; for the low postcode annual gas demand case there are no minimum endpoint violations, whereas this rises to three hours for the high annual gas demand case. As both scenarios are modelled with 100% penetration, this clearly demonstrates the impact of how locally-specific gas demand can result in different outcomes for an LV feeder when converting the existing gas demand to electrical heat demand.

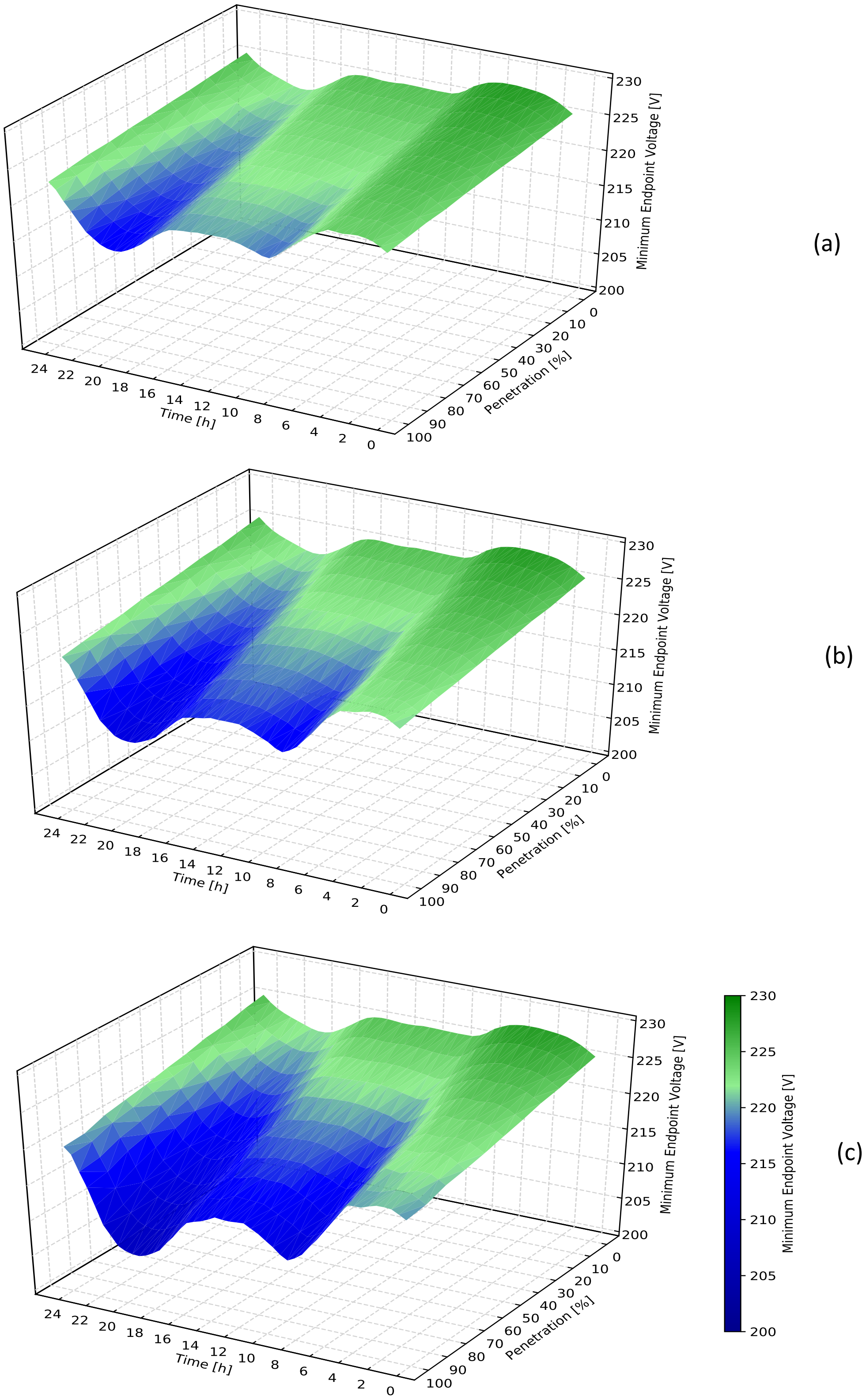


Figure 4-17 Average minimum endpoint voltage vs time vs penetration. (a) 9000 kWh (low) (b) 14000 kWh (RHPP – mean) and (c) 19000 kWh (high)

	9000kWh (low)	14000 kWh (RHPP – mean)	19000 kWh (high)
Number of violations (hours)	0	1	3

Table 4-3 Number of violations (hours) for 9000 kWh (low), 14000 kWh (RHPP – mean) and 19000 kWh (high) cases at 100% penetration

As demonstrated in Figure 4-17, the variations in heat demand have the potential to influence at what penetration of HPs voltage violations are likely to occur and the subsequent severity. Therefore, in using the standard RHPP-mean approach, as is currently common practice, the true scale of HP impact may be heavily over/under-estimated which would feed into DNO network planning and management decision making. This may translate to an over/under-estimation in the scale and cost of the solution necessary to support HP uptake and ensure reliable network operation. This also may influence decision making with regards to the appropriate solution and when it should be deployed i.e. adopting a flexible management approach in the interim with a view of reinforcing in the future or deploying a fit for purpose flexible solution for the long-term. Fundamentally, the results presented emphasise the scale of impact from variations in heat demand on the network and the value of this methodology in its ability to capture these variations.

4.7 Discussion

The chapter has demonstrated a robust and easily scaled methodology for deriving a local heat demand, and therefore local electrical heat load, from a single annual gas demand figure, enabling the calculation of localized daily winter demand for temporally sparse datasets. The core annual to daily demand translation methodology was tested using a common process and fit parameters for three heat-type demands, and a range of customer population sizes, with a MAPE below 10% for population sizes of 25 and greater.

This work circumvents the requirement to obtain detailed building, demographic, and behavioural parameters in order to construct a bottom-up model of local heat demand. This approach has been shown to be insensitive to size of customer or specific heat demand type. By drawing on a geographically granular dataset, combined with the developed methodology for improving temporal resolution of heat-type demand data the existing reliance on pure heat pump trial data for modelling electrical heat load at LV scale can be reduced and instead augmented with locally sensitive demand data.

A key strength of this model is its insensitivity to specific heating system type. Therefore, this approach can be adapted to predict future local electrical heat demand for air source heat pumps, ground source heat pumps or even electrical combi boilers as long as appropriate model inputs for conversion efficiencies are used.

In the case of the RHPP dataset, at the time of writing it is now approaching nine years since the initial trial data was captured [115]. Trial data remains essential to examine and validate population level effects that are difficult to model using conventional physical approaches – this will be supported by the upcoming BEIS Electrification of Heat Demonstration Project which will collect demand data from a further 750 domestic heat pumps [77]. However, even the most up to date trial data represents a limited geospatial and temporal view of locally variable demand influences and the methodology offered in this paper presents a way of complementing the value provided by heat pump trial data.

This work directly builds on the heat pump modelling approaches outlined in [76] [153] [78], which all construct averaged demand profiles from limited trial datasets. As has been highlighted by the authors in [76], a key outstanding issue with these approaches was the difficulty of rescaling findings to new target areas. This issue is not constrained to electrical heat load modelling and reflects a wider issue in the literature for modelling new load types at distribution network level, where modelling efforts are often constrained by limited and aging trial data.

Through the ADMD and network impact assessment case studies, the variation in final electrical heat load due to local heat demand has been demonstrated. From a pure ADMD perspective, a one standard deviation shift in input local annual gas demand has been shown in this chapter to translate into a 20% shift in predicted local ADMD. Therefore, whilst existing datasets provide an average view of potential electrical heat load, they do not reflect the real diversity of potential electrical heat loads present in the overall population.

Similarly, the network impact case study demonstrates the variation in average endpoint voltage versus time of day and penetration level of heat pumps. The average case from the RHPP dataset alongside example high and load gas demand cases are plotted, with average minimum endpoint voltage shown to strongly correlate with the three electrical heat scenarios shown. This demonstrates the potential variation from the mean when comparing highly aggregated electrical heat pump load obtained from geographically distributed trial data, as opposed to localised results for specific geospatial clusters of physical and behavioural parameters.

The developed conversion model is dependent on the core assumption that annual mean gas consumption at a postcode level can be translated into an equivalent hourly electrical heat load using the use of simple linear conversion efficiencies. Whilst a gas central heating system and electric heat pump driven system both are designed to output heat to achieve the desired room temperature for occupants, the switch from fossil-fuel fired to electrically supplied heating can have behavioural implications that impact final energy consumption. [172] explored the concept of a rebound effect for households introducing improved energy efficiency measures, and whether decreased costs to achieve a nominal thermal comfort level resulted in a corresponding increase in energy usage as occupants made use of increased savings. More recently, [173] estimated that economy-wide rebound effects could erode more than half of anticipated energy savings gained from efficiency improvements. The evidence base for this phenomenon is still developing however, with limited specific understanding of how this effect would manifest for households adopting heat pumps.

Within the UK, many residential premises do not have a connection to a domestic gas grid (off-gas) [174] and therefore the developed method cannot be directly applied to derive a local demand due to the lack of gas data for off-gas households. However, there are modifications that can be made to this approach to facilitate examination of local heat demand for off-gas networks in order to assess LV network impact. Off-gas postcodes could be paired to gas postcodes with similar physical and demographic features, or similarly off-gas heat demand could be estimated based on regional or sub-regional magnitudes. Whilst the specific approach would be subject to the availability, quality, and relevance of supporting datasets, this would provide further insight into localised electrical heat load where presently only highly averaged estimates exist.

4.8 Conclusion

This work develops a composite model that harnesses the information encoded in the geographically granular postcode level annual gas demand published by the UK Department for Business, Energy & Industrial Strategy (BEIS) [16] and leverages existing relationships in more temporally detailed but less geographically granular gas, direct heat and electrical demand datasets. This enables the use of existing geographically granular, temporally low-resolution datasets to scale electrical heat demand magnitude sensitive to local conditions. This scaling methodology may then be coupled with existing heat demand models or trial datasets which provide heat demand shape information. This supports distribution network operators with optimising network investment and identifying risks in the presence of uncertainty surrounding EHP uptake.

At present, gaining LV network load insights sensitive to geospatially variable parameters is a key issue for DNO's, as evidenced by the current emphasis of industry innovation projects focusing on improving distribution network visibility at the 11kV level and below [175] [176].

By exploiting the periodic nature of seasonal heat demand, a regression model has been contributed here from three sources of heat demand data and used to construct a predictive relationship between annual and seasonally variable daily demand. This relationship enables the use of temporally low-resolution, geographically high-resolution datasets such as the BEIS Postcode Level Gas Demand for localised heat demand prediction, leveraging the geographically granular physical and behavioural information encoded in the dataset. This demonstrates a hybrid approach that uses the high temporal granularity of exemplar data combined with the geographical scale granularity of a target dataset in order to maximise the usability for LV specific applications where localised sub-daily temporal resolution is required. From the examination of annual to daily demand for gas, heat and electric demand, the expectation is that this regression model can be applied to any heating technology that is proportionally sensitive to ambient temperature. Beyond the specific context of this work, the developed methodology demonstrates the value in synthesising geodemographic data from multiple sources in order to obtain localised insights for distribution network load under various scenarios for hypothesised LCT penetration scenarios.

Chapter 5

Disaggregation of Electrical Heat Load from LV Substation Load

This chapter presents an approach for disaggregation of electrical heat load from aggregated LV transformer data, facilitating the extraction of electrical heat load from existing LV sensors without the need for additional monitoring capability. This improves network situational awareness with respect to electrical heat load.

5.1 Summary

Whilst efforts are underway in order to forecast heat pump uptake and the consequent load and magnitude effects on existing distribution network assets, the limitations of using trial data and supplementary datasets means that there will always be a differential between the electrical heat demand as modelled and the actual electrical heat demand on a specific feeder. The transition to target levels of heat pump uptake will take time and tools will be required in order to support the intermediate period of early and mid-technology uptake. This chapter seeks to overcome this difficulty by developing a methodology for the disaggregation of electrical heat load from LV substation data in order to extract locally specific electrical heat demand. This facilitates the examination of heat pump electrical demand and penetration on a feeder without the need for additional hardware monitoring capability. In turn, this then enables possibility of flexibility type assessment for the additional heat pumps on a network. A disaggregation technique to extract electrical heat load from aggregated heat and non-heat load is tested and applied on test data synthesised from electrical heat pump and smart meter trial data with the error quantified.

5.2 Introduction

Within the UK, electrical heat pump uptake is only a fractional part of the long-term strategic target imposed by the UK government's Heat and Buildings Strategy. The ambition for 2028 is to support the installation of 600,000 heat pumps per year [38], whilst in 2019 less than 1% of English housing stock had a heat pump for space and/or water heating [177]. There has been extensive work performed to date on the subject of electrical heat load modelling with sensitivity to various parameters, both as featured earlier in this thesis as well as in the wider literature. This has encompassed modelling the effects of increased domestic electrical heat pump penetration on distribution networks drawing on existing trial datasets or constructing physical models that reflect parameters of typical households and associated heating systems.

Whilst these works provide indicative predictions for future electrical heat load, the reality is that there will inevitably be a gap between the heat load forecasted by a model developed from generic datasets and the actual electrical heat load imposed on a specific feeder due to increased heat pump penetration. As the progression to high penetrations of heat pump technology will not be instantaneous, distribution network operators will require tools to support with the ongoing adoption of heat pumps at the LV level.

LV networks are traditionally designed with very low levels of communication and control, which was complementary to the needs and function of the historic LV network. Typically, the substation transformer is the only point of visibility on the distribution network, and this represents an aggregated view of the voltage and current characteristics of all of the downstream loads. Historically this level of monitoring has been sufficient for day-to-day management and future network planning. However, the increased uncertainty associated with heat pumps and new LV connected low carbon technologies in general presents the risk that lack of visibility surrounding increased electrical heat load presents a threat to existing and future network assets.

This work seeks to develop and demonstrate a methodology for disaggregating electrical heat load from the aggregated load at the point of the LV transformer, facilitating improved understanding of the connected load characteristics and future decision making. The presence of partial heat pump presence on a network presents several opportunities for improving decision making at both the planning and operational level. By enabling access to locally specific electrical heat load, future impacts due to increased local heat pump penetration can be improved whilst being supported with the generically developed electrical heat load models.

Similarly, by understanding the dependencies of the connected electrical heat pumps, participation in a flexibility type scheme can be addressed for that specific feeder. Finally, there is also the opportunity to extract local electrical heat load from neighbourhoods with more advanced levels of penetration to support estimation of network impacts elsewhere.

5.3 Aims and Objectives

On this basis, the contribution of this chapter is to address the gap presented by generic development of electrical heat load and develop a methodology for extracting locally specific electrical heat load from aggregated LV transformer data. This enables the future coupling of generically developed models with locally specific insights in order to support the future planning and operation of power distribution networks.

5.4 Literature Review

Load aggregation and disaggregation techniques have been applied extensively in the wider research literature for a variety of applications, including signal processing and other data conditioning tasks where level of detail is traded off versus ease of model computation [178]. In an energy specific context, disaggregation has been the subject of research for developing various techniques to support non-intrusive load monitoring for power system applications [179]. For power distribution networks, significant research focus has been applied to the problem of disaggregation of household appliances from smart meter data [180].

This has in part been driven by the increasing uptake and availability of smart meter data [46], combined with increasing levels of interest in characterisation of household energy usage alongside increased future uncertainty surrounding low carbon technology uptake and usage [21]. Non-intrusive appliance load monitoring (NIALM) techniques have been developed to differentiate household appliances from aggregated smart meter data, facilitating higher fidelity analysis of household energy consumption without the need for additional monitoring capability [181]. Additionally, monitoring of household energy usage through a single household meter as opposed to appliance specific meters is more palatable for stakeholders. A range of NIALM techniques have been developed in order to take raw household smart meter data and disaggregate this into constituent household appliance loads in order to provide improved insight onto time of use and power contributions of various domestic appliances. Initial works were based on simple edge detection methodologies to indicate whether known appliances were in the “on” or “off” state [182]. Increased sophistication and data-processing capabilities has led to more advanced disaggregation methodologies. [183] utilised hidden Markov Models with segmented integer quadratic constraint programming to disaggregate household power at an average frequency of 0.3Hz into the appliance level. However, the utility of these insights has been limited by lack of practical implementations. In order to exploit knowledge of household-level appliance usage in a networks context, computational overheads combined with complexity of integration compared to the yet to be quantified benefits of appliance-level knowledge must be overcome.

In contrast, disaggregation of load types at the substation level has not yet extensively been examined. Despite the high rates of smart meter deployment at the distribution network level within the UK, with household adoption at 51% as of March 2022 [46], DNO system observability is presently constrained by default to substation-level or higher monitoring. Whilst energy suppliers have access to smart meter data for billing purposes, DNO’s do not have equivalent access due to the legal separation of DNO and energy supplier functions within the UK [184]. This situation is evolving however, with Office of Gas and Electricity Markets (Ofgem) approval of UKPN [185] and SSE [186] proposals for use of anonymised smart meter data, with further recommendations to treat smart meter data as “presumed open” [187].

Therefore, LV asset monitoring is typically performed at the point of the LV transformer, providing a single set of voltage and current measurements that represents the aggregation of up to hundreds of households. This has been suitable for historic DNO function, but the uptake of new load types such as electrical heat pumps combined with electric vehicles and rooftop solar will impose changes on LV network energy and power profiles. The integration of these new low carbon technologies will also be accompanied by the introduction of more sophisticated network operation and control techniques, to facilitate the planning and operation of the future LV distribution network. In order to minimise physical network intervention in the presence of uncertain future technology uptake, it is desirable to develop techniques for maximally understanding present and future network conditions without the need for significant additional hardware monitoring.

[188] demonstrated the case for developing disaggregation techniques for MV distribution networks, characterised by higher levels of monitoring and control in comparison to LV networks.

5.5 Problem Overview

Due to the nature of LV transformer load in a distribution networks context, there are several constraints to be accounted for when developing a disaggregation methodology for this application. These can be grouped as constraints determined by the LV transformer as well as constraints imposed by the specific problem of electrical heat load disaggregation. These constraints inherent to the LV network and are not specific to the selected aggregation methodology.

The LV transformer places limitations on the observability of the overall network and, in turn, the observability of connected electrical heat load. Typically sampling frequency is in the region of half hourly due to alignment with the 30-minute settlement period for electricity markets [189], therefore whilst bulk demand trends can be observed, high frequency events or load switching is not visible and therefore cannot be exploited as model input features. A typical LV transformer is responsible for supplying on the order of one to a few hundred households, which therefore means the operating region spans from the very low to the moderately high levels of aggregation [190] . With reference to the ADMD curve in Love [76] and in previous chapters, LV network operation exists along the knee of the ADMD curve where the rate of change versus number of customers is highest. This necessitates the ability to be able to sufficiently disaggregate electrical heat load for aggregated demands with low diversity as well as high diversity.

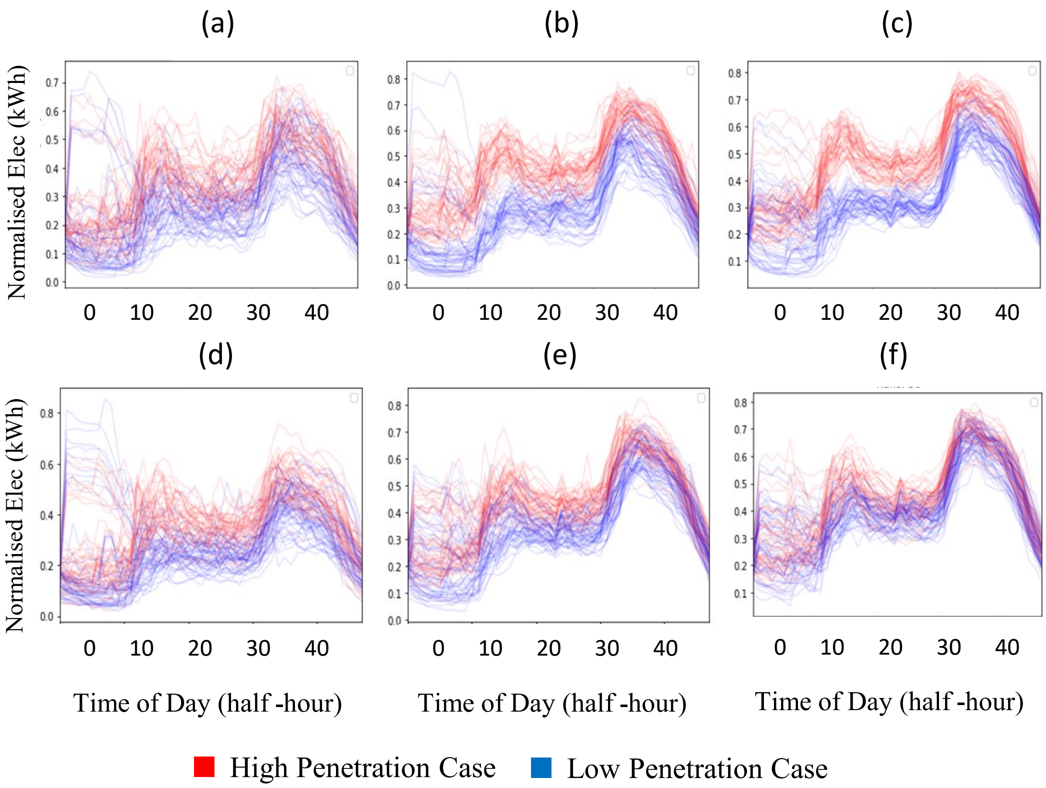


Figure 5-1 Normalised heat and non-heat daily load shapes for high and low penetration cases; (a) 5 customers, 100 and 1% penetration (b) 15 customers, 100% and 1% penetration (c) 25 customers, 100% and 1% penetration (d) 5 customers, 75% and 25% penetration (e) 15 customers, 75% and 25% penetration (f) 15 customers, 75% and 25% penetration

The behaviour of electrical heat type load with respect to non-heat load places further restrictions on the problem approach. Figure 5-1 demonstrates the seasonal variation for heat, non-heat and aggregated load for a group of 25 customers. Broadly it can be observed that whilst the heat load features a stronger seasonal dependency, both heat and non-heat load follow the same general seasonal trends. Similarly, Figure 5-4 demonstrates the time of use characteristics for heat and non-heat load over a ten-day winter period. Again, the time of use characteristics for heat and non-heat load exhibit a strong correlation. This is to be expected due to the positive correlation with household activity for both heat and non-heat appliance usage; appliance and heating usage will be at its highest during hours when residents are at home.

Therefore, any disaggregation technique to be applied must be able to extract features specific to electrical heat demand whilst overcoming the similarity of time of use and seasonal variation of non-heat load, as well as the diversity difficulties when operating in an LV type environment. This functionality must take into account the range of number of customers typically connected to a LV feeder, the range of possible electrical heat pump penetrations ranging from zero to one hundred percent and the feasible range of local temperatures for the target area in question. This must also be able operate with the limited observability constraints of an LV transformer.

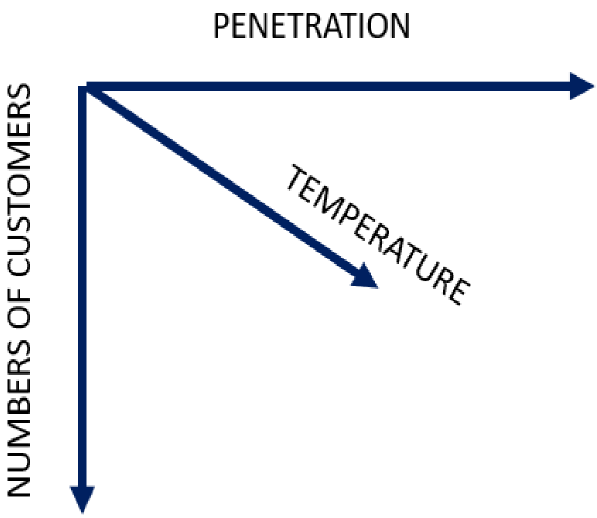


Figure 5-2 Axes of dependencies

Furthermore, there are the difficulties associated with the time of use similarities for heat and non-heat load types. Figure 5-1 demonstrates the similarity between normalised half hourly shapes for a range of customer group sizes and penetration cases. It can be observed that for the 25% and 75% penetration cases demonstrated, there is a very close similarity in half hourly load shapes. For the 1% and 100% cases, there is a slight deviation in normalised half hourly magnitude but there otherwise remains a close similarity in load shapes. Therefore, when attempting to infer the electrical heat penetration on an LV feeder through data-driven techniques, then additional input features beyond half hourly shape must be exploited in order to provide a result with sufficiently small error and translatability outside of the original training datasets.

Therefore, to summarise, the model design must be able to accommodate for the following constraints:

- **Sampling Frequency:** Suited for use with data of 30 minute sampling frequency
- **Low to High Diversity:** The methodology must be adaptable to a wide range of customer diversity, typical of LV network applications, encompassing scenarios form extremely low to high diversity.
- **Low to High Penetrations:** Need to be able to manage robust disaggregation for varying penetrations of heat pumps; low penetrations versus high penetrations will have significantly different impacts. Low penetrations with limited impacts will be of lesser interest compared to high penetration feeders, but the ability to differentiate between different penetrations is required.
- **Temperature Range:** Heat pump usage and demand magnitude varies on a seasonal basis; therefore the disaggregation methodology must be able to differing usage profiles for the same equivalent penetration
- **Shape Insensitive:** High similarity between heat and non-heat load shapes means the designed approach needs to exploit other features rather than load shape and magnitude.

On this basis, any selected methodology must be able to overcome the similarities in shape and time of use activity for heat and non-heat load in order to accommodate a broad range of conditions associated with LV networks. The selected limits are defined in Table 5-1. The possible EHP penetrations of interest are bounded from 0% to 100%, capturing the range between no EHP uptake on a feeder and full EHP uptake for all households. The temperature range of interest has been bounded between 0°C and 25°C. The lower 0°C limit is constrained by the range captured between electrical daily demand and external daily average air temperature in Figure 3-3, derived from RHPP data [115] and the Central England daily temperature series [132]. Below 0°C is an operational zone of interest due to the decrease in achievable COPs in this region, but the lack of EHP trial data for this region limits the validation and analysis that can be performed. Finally, the numbers of customers of interest has been defined as ranging from 1 to 75. The lowest bound has been set at 1 as the lowest practicable number of customers on a feeder, whereas the upper limit has been set at 75 to reflect point at which the ADMD curve has been observed to stabilise in the RHPP dataset via [76]. This represents the number of customers required for the effects of diversity to result in the aggregated electrical heat load shape to converge.

Parameter	Minimum	Maximum
EHP Penetration (%)	0	100
Temperature (degC)	0	25
Number of Customers	1	75

Table 5-1 Parameter minimum and maximum limits for disaggregation study design

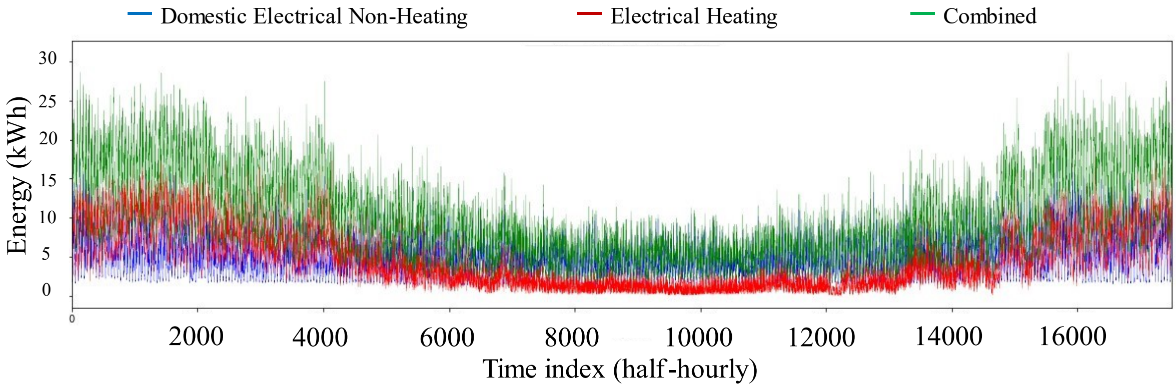


Figure 5-3 Twenty customer feeder with 100% electrical heat pump penetration; one year period with half hourly resolution

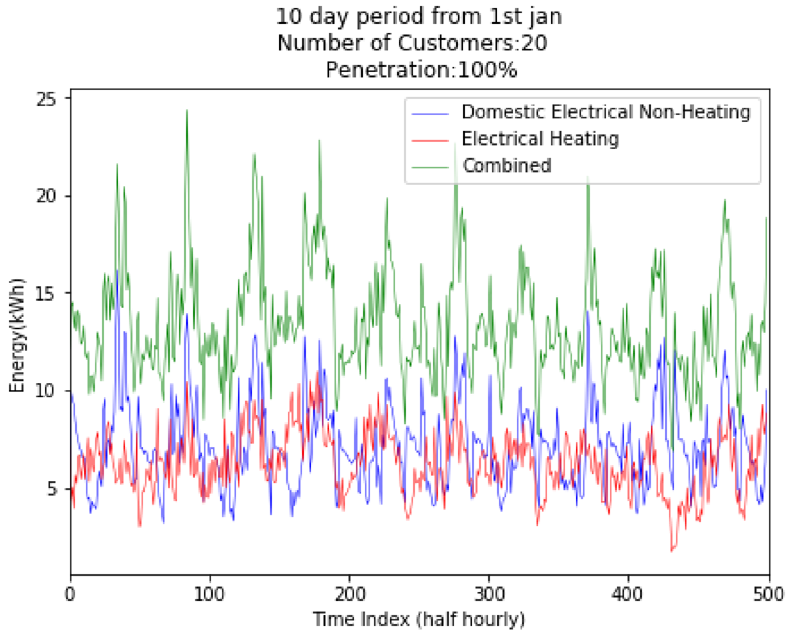


Figure 5-4 20 Customer feeder with 100% electrical heat pump penetration; 10 day winter period with half hourly resolution

5.6 Methodology

This work describes a methodology for disaggregating electrical heat load from the aggregated load data collected at the point of an LV transformer within the distribution network. The overall work can be broken down as follows:

- Construction of synthesised training datasets in order to form the aggregated LV transformer load for model testing
- Definition of disaggregation methodology and accompanied features for applying to constructed aggregated load
- Test and cross-examination of disaggregation methodology with respect to temperature, penetration and number of customers

Existing smart meter and electrical heat pump data is used to construct synthesised test data that forms the aggregated LV transformer load for test. The disaggregation methodology is tested versus sensitivity to temperature, number of customers and heat pump feeder penetration.

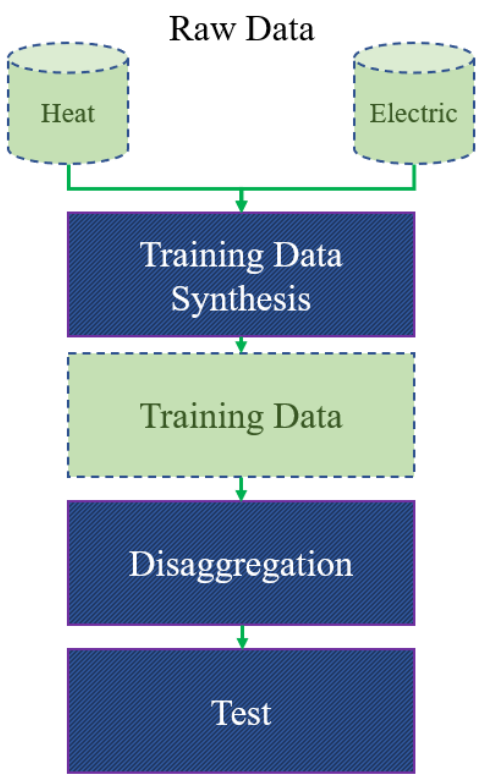


Figure 5-5 Methodology overview for disaggregation of electrical heat load from transformer load

5.6.1 Training Datasets and Aggregated Load Synthesis

This work makes use of two datasets in order to synthesise the aggregated LV transformer load, prior to application of the developed disaggregation techniques in order to extract electrical heat from non-heat load. Due to the lack of a comprehensive dataset featuring domestic load combined with electrical heating, two datasets as used to synthesise an aggregated load. The first dataset consists of smart meter data obtained from the EDRP dataset [158]. This dataset is used to provide the domestic non-heat load for the study. The second dataset consists of the electrical heat pump demand data from the RHPP dataset and is used to provide the electrical heat demand data for the study. The RHPP dataset was selected as it remains the largest publicly available electrical heat pump dataset within the UK. The relationship of these datasets is illustrated in Figure 5-5; for a feeder with a given number of connection’s, electrical heat is paired with smart meter data for each customer and then summed in order to provide an aggregated LV transformer load for test. For simplicity technical losses including resistive and reactive losses are not included in this study.

The developed methodology is tailorable to number of customers, and percentage level of EHP penetration amongst the total customer group. The aggregated load at the point of the transformer can be represented as in (47), where $Load^{TX}$ is the aggregated load at the transformer which is the summation of the total customer loads n connected on the feeder. This can be expressed further as in (51), where the aggregated load at the transformer is the summation of customer heat-type electrical load and non-heat type electrical load present on the feeder. The addition of a penetration factor $\emptyset$ in (49) which varies from 0 to 1, reflects the corresponding EHP penetration level from 0% to 100% for the feeder under consideration (50).

$$Load^{TX} = \sum_{i=1}^{n} Load_i \tag{47}$$

$$Load^{TX} = \sum_{i=1}^{n} Load_{heat} + \sum_{i=1}^{n} Load_{non-heat} \tag{48}$$

$$Load^{TX} = \emptyset \sum_{i=1}^{n} Load_{heat} + \sum_{i=1}^{n} Load_{non-heat} \tag{49}$$

$$P(\%) = \emptyset \times 100 \tag{50}$$

When constructing an aggregated load consisting of a defined number of customers n with defined EHP penetration level $P(\%)$ the following process is applied. n random samples are obtained from the non-heat type electrical load EDRP dataset, with a further n x $\emptyset$ samples obtained from the heat-type electrical load RHPP dataset, rounded up to the nearest whole number. RHPP customer data is resampled from 2-minute to 30-minute intervals so that the sampling frequency is consistent with the 30-minute sampling frequency of the EDRP dataset. As sampling windows vary across as well as within the RHPP and EDRP datasets, the randomly sampled profiles are aligned by day of year so that the seasonality of both load types are aligned. The obtained heat and non-heat electrical load profiles are then summed for each 24-hour period over a 365-day period beginning on January 1st and ending on December 31st in order to provide the synthesised aggregated transformer load $Load^{TX}$. Whilst the number of customers n and penetration level $P(\%)$ will be varied as model inputs for the disaggregation process, the methodology for constructing the synthesised aggregated load will remain the same for any variation in model inputs.

5.6.2 Disaggregation Theory

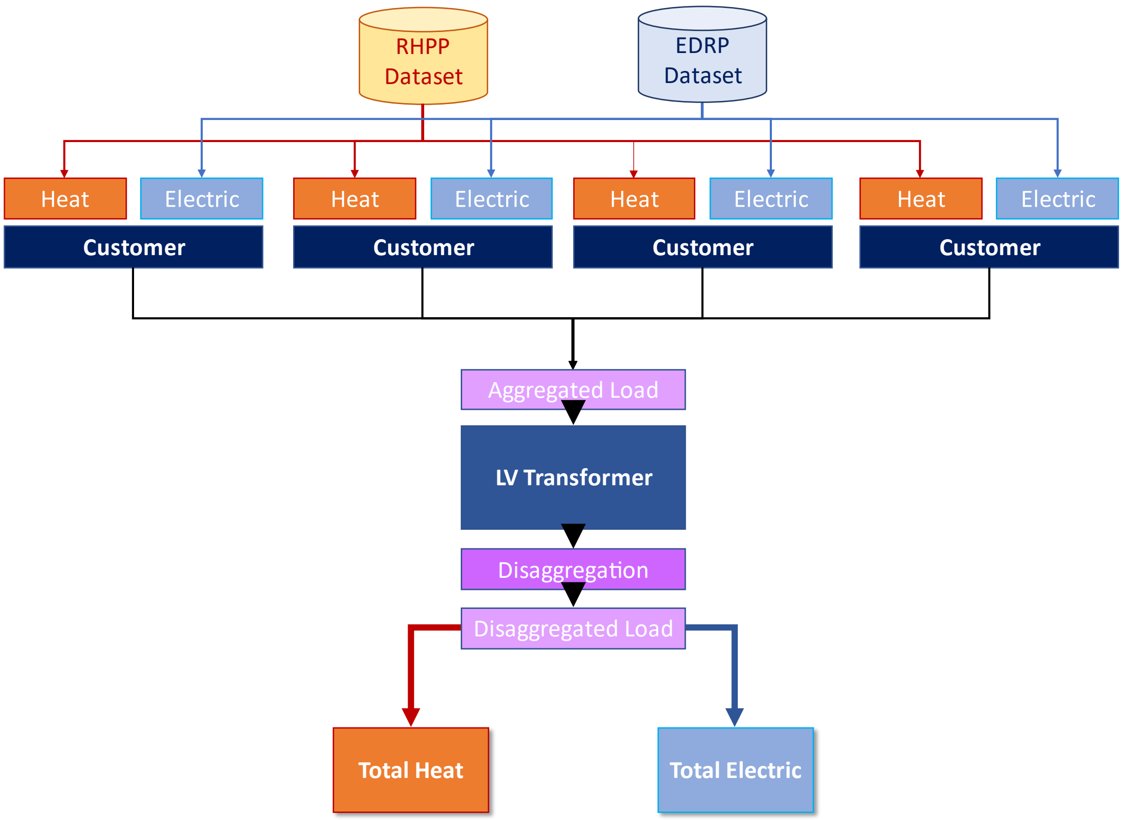


Figure 5-6 Overview of synthesised load data coupled at point of LV transformer

Figure 5-6 diagrammatically shows a synthesised aggregated transformer load for four customers, each consisting of a heat-type and non-heat type load profile obtained from the RHPP and EDRP datasets respectively. This section will discuss the process for disaggregation of the summed heat-type electrical load from the aggregated heat-type and non-heat type load at the point of the LV transformer.

5.6.2.1 Base Summer Load Subtraction

The Base Load Subtraction feature is constructed on the basis of two assumptions. Firstly, that domestic non-heat load is largely static in contrast to temperature-sensitive, and consequently seasonally variable heat-type load. Heat-type load for this study will only include electrical heat load used for space heating and does not include electrical heat load used for hot water. Typical household energy consumption has been estimated at 4.3kWh per day by the Energy Saving Trust [191], whereas the median maximum energy consumption due to EHP load from the RHPP dataset is measured at 35.25kWh per day [115]. The RHPP dataset measures hot water energy consumption distinct from heating, but only 22 of the 700 customers actually return nonzero values for this field. Given the limited hot water energy consumption in the RHPP dataset, combined with the unknown contribution to energy consumption in the EDRP dataset [158], and that hot water energy consumption this method does not attempt to account for the effects of hot water heating. For winter extremes the contribution of hot water heating will be relatively small compared to space heating, but this does mean that for warmer cases the effects of hot water will not be accounted for.

Non-heat domestic load incorporates a range of loads including domestic appliances, lighting and entertainment devices. Secondly, that heat-type load usage during summer months is functionally zero. The load at the LV transformer $Load_{Summer}^{Tx}$ can be expressed generically as shown in (51), where the aggregated load is a function of the simultaneous heat and non-heat load applied to the transformed. During summer months where heat load is at its seasonal minimum, the heat-load may be assumed to be zero as per (52) and the remaining measured load at the transformer is equivalent to the connected non-heat load on the network.

$$Load_{Summer}^{Tx} = Load_{Summer}^{Non-Heat} + Load_{Summer}^{Heat} \tag{51}$$

$$Load_{Summer}^{Tx} = Load_{Summer}^{Non-Heat} + 0 \tag{52}$$

During the Winter months, the $Load_{Non-Heat}^{Summer}$ value obtained during the Summer case may then be utilised as per (53). This posits that the aggregated transformer winter load $Load_{Winter}^{Tx}$ minus the measured summer non-heat load $Load_{Summer}^{Non-Heat}$

$$Load_{Winter}^{Heat} = Load_{Winter}^{Tx} - Load_{Summer}^{Non-Heat} \tag{53}$$

Whilst simplistic, this methodology is advantageous as it provides a transformer specific estimation of heat-load from the obtained $Load_{Summer}^{Non-Heat}$ parameter without the need for external training data of unknown translatability. However, this technique is constrained by the fact that non-heat load is not truly static on seasonal timescales due to increased household occupancy and appliance usage during Winter months. Therefore, this will result in a limitation for the minimum achievable error using this technique.

5.6.3 Model Inputs

As has been discussed earlier in 5.5, the developed disaggregation methodology is designed to facilitate the estimation of electrical heat load for a range of EHP penetrations and customer group sizes relevant to the typical quantities found on an LV feeder. The model inputs consist of the number of customers on a feeder n, alongside the defined percentage penetration of how many customers on that feeder are equipped with EHPs. $P\ (\%) = 100$ represents all customers on the feeder for a defined group size being equipped with an EHP, whereas $P\ (\%) = 0$ would reflect zero penetration of EHP's on an LV feeder.

$$inputs = \begin{cases} n = \{5,10,25,50,75,100\} \\ P\ (\%) = \{1,25,50,75,100\} \end{cases} \tag{54}$$

5.6.3.1 Test Matrix

The following penetration and total number of customers connected to a transformer in Table 5-2 are applied to test the disaggregation methodology for a range of scenarios. This spans the possible range of penetrations and encompasses customer group sizes from low to high levels of aggregation.

Customers	**Penetration (%)**				
5	1	25	50	75	100
10	1	25	50	75	100
25	1	25	50	75	100

50	1	25	50	75	100
75	1	25	50	75	100

Table 5-2 Test Matrix for Number of Customers n and Penetration P (%)

5.6.4 Validation

5.6.5 Metrics

A number of standard and custom metrics will be used for this work. Standard metrics allow for comparisons between this work and others. Custom metrics are useful for demonstrating model functionality in accordance with its specific strengths. Due for the need to compare model effectiveness across a range of penetrations and customer numbers, with consequently different seasonal minimum and maximum amplitudes, scale invariant metrics such mean absolute percentage error are preferred.

Additionally, a novel metric capturing how well the relationship between the time of year and heat load is represented is described.

5.6.5.1 Peak Daily Percentage Error (Median) (%)

The percentage error δ between the expected electrical heat load for a point in time v_e and actual electrical heat load for a point in time v_a is expressed as in (55).

$$\delta\ (\%) = \left|\frac{v_a - v_e}{v_e}\right| \cdot 100\% \tag{55}$$

For each combination of n and P (%), heat and non-heat electrical load profiles are randomly sampled as required from the RHPP and EDRP datasets. Further to this, for each combination of n and P (%), multiple random samplings are obtained to construct multiple aggregated loads. The peak daily percentage error δ_{peak}^{daily} is for each result set is calculated as per (56), where $v_{a,t}$ reflects the actual electrical heat load at time t, and $v_{e,t}$ reflects the estimated disaggregated electrical heat load at time t. Then the overall median M_δ (%) for a n,P (%) input of 50 random samplings obtained as per (57).

$$\delta_{peak}^{daily}(\%) = max_{t \in T} \left| \frac{v_{a,t} - v_{e,t}}{v_{e,t}} \right| \cdot 100\% \tag{56}$$

$$M_\delta(\%) = \frac{\delta\left[\frac{n}{2}\right] + \delta\left[\frac{n}{2}+1\right]}{2} \tag{57}$$

5.6.5.2 Day Angle Rate of Change and Intercept

Rather than use direct historical temperature as a model input, this work uses day angle as a proxy to reflect the seasonal temperature variation. As has been discussed in Chapter 3 the relationship between daily average demand and daily average temperature can be represented as a linear relationship with non-linear behaviour at the extremes. The linear region for heat pump demand can be modelled as shown below, where (58) is the generic form for a linear relationship, and (59) shows the specific form for the relation between daily demand and temperature. Due to the lack of historical temperature unity for the paired heat and non-heat datasets, the relationship between day angle and daily demand will instead be modelled as an equivalent function.

$$y = mx + c \tag{58}$$

$$Daily\ Demand\ (kWh) = m \times Temperature(degC) + c \tag{59}$$

$$Daily\ Demand\ (kWh) = m \times Day\ Angle(°) + c \tag{60}$$

The day angle derived metrics therefore correspond to how well the disaggregated heat aligns with the true heat-load rate of change and intercept. The rate of change directly corresponds to how much heat load will vary on a seasonal basis, and the intercept determines the maximum expected load under extreme conditions.

$$m_{err\,(\%)} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{m_a - m_p}{m_a}\right| \tag{61}$$

$$c_{err\,(\%)} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{c_a - c_p}{c_a}\right| \tag{62}$$

As an alternative to pointwise metrics, this metric performs a comparison of how well the disaggregated data follows the real temperature dependent relationship of the actual data.

5.6.5.3 Estimated number of heat pumps and Penetration

Finally, a metric that reflects penetration level versus number of meters is proposed. Using the heat localisation model developed previously, an estimation of the required heat pump size can be made. Using an estimated average heat pump rating, once the heat load is disaggregated then an estimation of number of heat pumps installed on the network can be made. This provides an alternative to numerical comparisons, and offers a more interpretable estimate of predicted heat pump penetration versus estimated penetration. (63) illustrates the relationship between the maximum disaggregated demand $Dmax$, the defined maximum heat pump rating maximum and its relationship to the number of estimated heat pumps installed on the network. This can be then translated to an estimation of penetration as per (64).

$$n_{HP} = \frac{Dmax}{Rating\ Max} \tag{63}$$

$$P(\%)_{est} = \frac{n_{HP}}{n_C} \tag{64}$$

5.7 Results

5.7.1 Peak Daily Percentage Error (Median) (%)

	Penetration P (%)					
	1	**10**	**25**	**50**	**75**	**100**

Customers (n)	**5**	1831.5	5907.9	746.8	501.5	386.8	130.4
	10	7632.4	7043.4	707.2	287.5	111.9	48.3
	25	23804.2	2212.4	685.7	130.2	63.2	17.9
	50	28606.4	1365.4	303.9	90.3	32.2	14.6
	75	105729.3	759.4	217.1	78.2	29.5	1.4

Table 5-3 Peak Daily Percentage Error for Number of Customers and Penetration (%)

The results obtained for the Peak Daily Percentage Error (median) $M_{\delta}(\%)$ process as described in 5.6.5.1 is tabled in Table 5-3. There are some clear observations to be made. Low input values for n and $P\ (\%)$ result in excessively high values of $M_{\delta}(\%)$. As an example case, for the 1% penetration 5 customer scenario, a 1831% for $M_{\delta}(\%)$ could occur when actual electrical heat load is approximately 180kWh and estimated is close to zero. This is a natural weakness when using percentage error type metrics to compare actual versus expected values. For the 1% cases for customer groups between 5 to 75, this percentage error roughly scales proportional to customer group size, indicating that for extremely low EHP penetration cases there is a tendency to underestimate electrical heat load. Given the very low ratio of electrical heat load compared to non-electrical heat load, this results in a high error as anticipated using the methodology in 5.6.2.1.

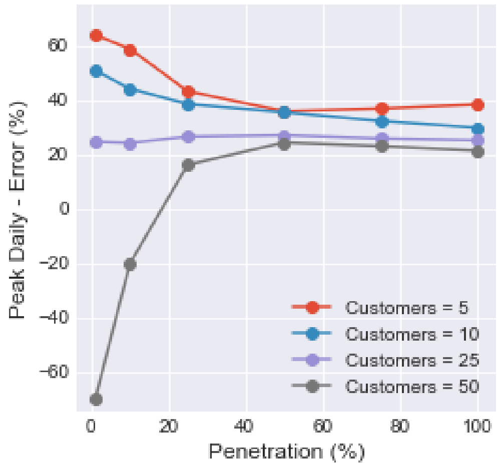
At the other extreme, the $P\ (\%) = 100$, n $=$ 75 scenario demonstrates a very low $M_{\delta}(\%)$ of 1.4. This has several implications; for high penetration cases such as this one, electrical heat load will be dominant compared to non-heat electrical load. Using the base summer load subtraction methodology used to estimate $Load_{Winter}^{Heat}$ in (53) then is a good approximation of aggregated electrical heat load on a feeder. Intermediate values for $P\ (\%)$ and n see increased percentage errors compared to the high $P\ (\%)$, n case result in a consistent under-estimation of electrical heat load.

5.7.2 Day Angle Rate of Change and Intercept

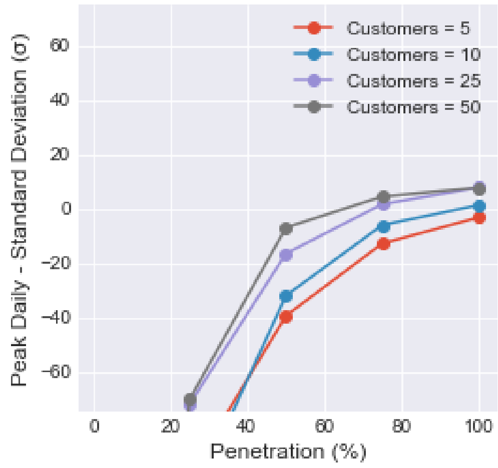
Figure 5-7 displays the results for the error metrics m_{err} (61) and c_{err} (62). These have been computed for customer group sizes 5, 10, 25 and 50 for the penetration (%) cases 1, 10, 25, 50, 75 and 100. Each customer group size and penetration combination has been constructed via random sampling of EDRP/RHPP non-heat/heat load pairs. Fifty random samplings are performed for each group size and penetration combination in order to provide an averaged result. Finally, for each group size/penetration combination, the error is calculated for each of the fifty random samplings. The peak $m_{err\ (\%)}$ for each set is plotted, along with the standard deviation.

The day angle error, $m_{err\ (\%)}$,reflects how well the slope, or seasonal rate of change, of the predicted electrical heat load matches the real electrical heat load. In Figure 5-7 (c) the $m_{err\ (\%)}$ converges close to zero for the 100% penetration, 50 customer case. This indicates that for customer groups that feature sufficiently high levels of diversity and where electrical heat load is dominant during winter worst case conditions, the disaggregation methodology is able to represent an appropriate slope that reflects the seasonal variation of electrical heat load. However, for low penetration/low customer number cases the quality of the slope estimation becomes particularly poor.

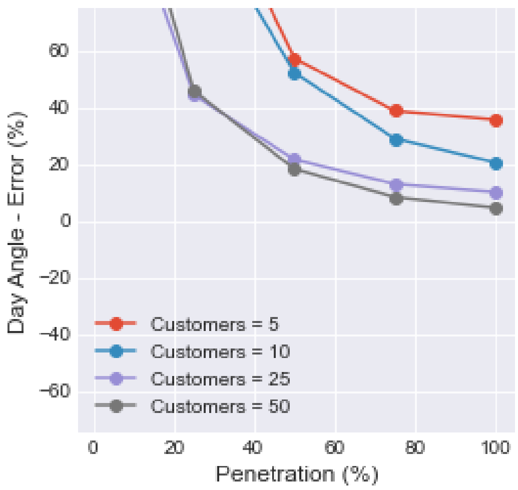
Figure 5-7 (a) represents the offset error $c_{err\ (\%)}$. This is a measure of how well the offset parameter captures the seasonal maximum of the estimated electrical heat load versus real electrical heat load. For the high-penetration/high -customer case, the error (%) converges on approximately 20 %. For 50 customers, this would equate to estimating the presence of 60 EHPs connected to the feeder rather than the true value of 50. However the offset error $c_{err\ (\%)}$ is relatively stable for penetrations of 20% and higher for all customer group sizes – this indicates there is a parameter that scales proportionally with customer group size that is contributing to a fixed percentage error. This potentially could be the contribution of energy consumption due to hot water heating that is imposing a fixed percentage error between the predicted and real electrical heat load.



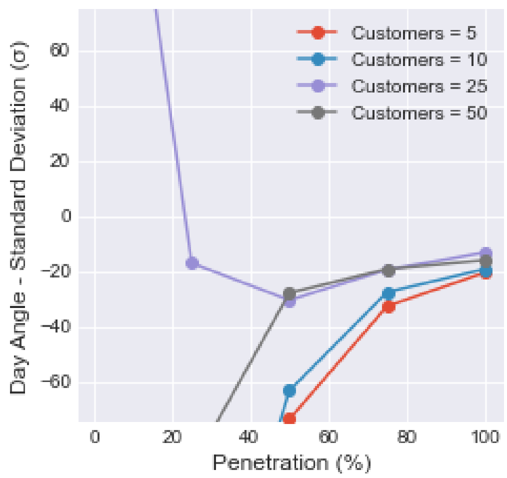
(a)



(b)



(c)



(d)

Figure 5-7 Peak Daily Percentage Error (a), Peak Daily Standard Deviation (b), Day Angle Percentage Error (c) and Day Angle Percentage Error (d) for customer group sizes of 5,10,25 and 50 for penetrations of 1%, 10%, 25%, 50%, 75% and 100%

5.7.3 Estimated number of heat pumps and Penetration

The equivalent estimated number of heat pumps for each P (%), n case is tabled below in Table 5-4. Given the disproportionately high percentage errors obtained by the metric using 5.6.5.1, this offers an alternative EHP penetration specific metric that demonstrates the estimated number of EHP devices connected on a feeder versus the actual configured value for the aggregated dataset. In this case, the predicted number of EHP devices tends to overestimate the true number of devices. However, as a very rough order of magnitude it provides a qualitatively closer indication of EHP penetration than the percentage-type metric.

Number of Customers	5		10		25		50	
	True Mean	Predicted Mean	True Mean	Predicted Mean	True Mean	Predicted Mean	True Mean	Predicted Mean
Penetration (%)								
1	0	0	0	0	0	0	1	0
10	1	2	1	1	3	3	5	6
25	1	1	3	4	6	8	13	17
50	4	4	5	7	13	16	25	31
75	3	5	8	11	19	24	38	46
100	5	7	10	13	25	31	50	60

Table 5-4 Estimated number of HPs connected on LV feeder for customer group sizes 5, 10, 25 and 50 at penetrations of 1%, 10%, 25%, 50% and 100%

5.8 Discussion

This work has outlined several of the challenges associated with electrical heat load disaggregation at the point of the LV transformer and tested a methodology for performing disaggregation of electrical heat load.

Despite the simplicity of the disaggregation methodology, the estimated number of heat pumps presented via Table 5-4 provides a relatively close estimation of true EHP penetration on a feeder sensitive to the variation in penetration and customer group size for each scenario. This is in contrast to the percentage type metrics in Table 5-3 which result in extremely high peak percentage errors for low penetration/low customer group size type cases due to low estimated values being penalised disproportionately. 5.7.2 demonstrated that daily estimated electrical heat load could be approximated via the linear function provided in (60), however for the high-penetration/high customer group cases there remains a fixed offset in estimated versus actual electrical heat load. This will be a result of estimating peak electrical heat load $Load_{Winter}^{Heat}$ as the function of $Load_{Winter}^{Tx}$ and $Load_{Summer}^{Non-Heat}$. In actuality, $Load^{Non-Heat}$ will not be static over a full seasonal period; as this encompasses device usage such as lighting, entertainment systems and appliances, all of which will see greater utilisation during darker and colder winter months when occupancy will be higher.

There are naturally limitations with this approach that is imposed by the test data. As the household smart meter and electrical heat pump data is obtained from separate customers at separate times, the test data as synthesised does not fully represent the concurrent demand relationships that might be seen in a household paired with a heat pump. For future applications it may be possible to make better use of day of week and locally specific temperature features in order to differentiate between heat and non-heat load. Similarly, the adoption of electrical heat pumps in a neighbourhood may impact non-heat load shapes and time of use characteristics – therefore care should be taken to understand the consequences of this.

Whilst electric heat pumps form a key component of the UK heat decarbonisation strategy, they do not form the only source of electric heat. Resistive electrical heating is well established in UK rural households and similarly common in urban environments [177]. Due to the 30-minute sampling frequency and levels of customer aggregation it is not possible to distinguish between electrical heat pump load and resistive electrical heat load; therefore, this work is reliant on the fact that resistive heating is not particularly widespread in UK households and is trending to be phased out in future in favour of more efficient solutions such as heat pumps.

5.9 Further Work

This section describes a methodology that would be desirable to develop as a further piece of work. This disaggregation technique seeks to overcome the static limitations of the previously described technique and exploits the fact that heat-load and non-heat load both vary on seasonal timescales in phase with the orbit of the earth around the sun and corresponding variation in seasonal temperature due to axial tilt for high latitude countries [192]. The common phase of heat-load and non-heat load poses a difficulty when attempting to decompose the two load types.

This methodology will examine the variability of the aggregated transformer load on days where the daily temperature deviates from the seasonal average daily temperature. For this case, the aggregated transformer load can be considered as the sum of multiple components; the seasonal average components and the deviation from mean components. For each degree deviation from the seasonal average temperature, there is a corresponding change in heat and non-heat load. However, heat and non-heat load will demonstrate different proportional responses with respect to temperature.

$$Load_{Mean}^{Transformer} + Load_{Deviation}^{Transformer} = Load_{Mean}^{Non-Heat} + Load_{Mean}^{Heat} + T^{NH} * Load_{Deviation}^{Non-Heat} + T^{H} * Load_{Deviation}^{Non-Heat}) \tag{65}$$

By examining the daily demand deviation from seasonal average temperature from time series data, the heat-content of an aggregated load can be estimated and therefore the electrical heat pump penetration connected to a specific LV transformer. Due to time constraints, this has been left as further work.

5.10 Conclusion

This chapter has demonstrated and tested a methodology for performing the disaggregation of electrical heat load from aggregated LV transformer load, facilitating locally specific understanding of electrical heat load without the need for additional hardware monitoring or infrastructure. In turn, this enables the extracted locally specific electrical heat load to be applied in future network impact studies, for other areas of interest or to support the assessment of flexibility on the feeder.

This methodology offers an alternative to traditional NIALM techniques which are primarily designed to disaggregate load on an appliance level with high-fidelity data, and therefore might struggle with the conventional sampling frequency of LV transformers.

Looking forward, the primary objective would be to validate the developed methodology with real-world aggregated LV transformer data, incorporating a genuine heat and non-heat load component alongside contemporaneous weather data, instead of relying solely on synthesised heat and load data. This validation with real-world data would help refine the methodology further, improve its accuracy, and potentially make it more adaptable for various scenarios.

Chapter 6

Unification of Electrical Heat Load Modelling

This chapter provides the unified concept for the work presented in preceding chapters, presenting an implementation that combines generic electrical heat load models with a methodology for deriving feeder specific electrical heat load.

6.1 Introduction

The previous chapters in this work provided standalone methodologies for the modelling and prediction of electrical heat load. The first two chapters presented methods for electrical heat load prediction by deriving models from existing trial data and subsequently augmented by supplementary datasets. The previous chapter presented a process for deriving an electrical heat load model from operational LV substation data, bypassing the requirement for trial data to develop electrical heat load predictions.

As increasing levels of renewables penetration is achieved, with correspondingly increased operational complexity, DNO's will seek to move beyond the standalone predictions provided by historic trial data in order to maximally optimise network decisions. Conversely, due to data quality issues, limited sensor capability, and the pragmatic difficulties of data processing in a live operational environment, raw LV transformer data necessitates further conditioning in order to be robust enough for decision making purposes. Alongside this, whilst it is the DNO's responsibility to ensure security of supply at the LV level, this responsibility is complemented by the particular needs and plans of commercial, residential and civic organisations connected to a specific feeder or present in a locality. This chapter presents a unification of the previously developed concepts.

6.2 Rationale

As has been previously discussed in this work, there is a heavy reliance on trial data in order to inform potential future LV network effects due to the impact of increased renewables integration. Due to the cost and effort of implementing large scale trials, the number of datasets to draw on is limited, with the RHPP trial providing the only large-scale heat pump dataset publicly available in the UK. Monitoring for this trial concluded in 2015 [8], presenting a eight year gap between close of the trial and the present day. The gap between initial trial design and equipment commissioning is even larger, with RHPP heat pumps installed between 2009 and 2014. To put this in perspective, the proportion of UK energy supplied from low carbon sources in 2010 was 10.1% - a figure largely unchanged from 2000 [21]. Since the Climate Change Act of 2008, this proportion increased to 21.5% in 2020, with corresponding changes in the energy landscape at the commercial and individual level. The last ten years have resulted in more changes to the generation and distribution of electrical energy in the UK since the initial development of a unified electricity system [193]. These timescales are typical for large scale trials which require up front design effort to ensure alignment with long term strategic needs, household recruitment and installation as well as ongoing monitoring and analytical outputs.

Therefore, while trial data provides population-level insights into potential future electrical heat load, the following informational lags should be taken into consideration:

- Time; length of time elapsed between trial data capture and target area of study. Corresponding changes in building construction, heat pump performance, household energy consumption and user behaviours due to the passage of time.
- Space/spatial variability; the geospatial distance between the area of trial data capture and the target area of study. Climatological differences, demographic differences, urban/rural variation.

Work in previous chapters has sought to reduce the temporal and spatial differentials between trial data and a target feeder, through scale localisation of trial data derived models using contemporary gas demand datasets. However, there are inevitably limitations with this approach. Due to the limitations of trial data for the model construction, temporal and spatial differentials cannot be fully eliminated. Furthermore, developed methods inform potential electrical heat load across a range of penetrations, but cannot provide information about notional future penetration.

Whilst there is a wide body of literature surrounding the modelling and prediction of future renewables penetration, this literature in itself remains demonstrative of future penetration versus various parameters rather than providing definitive outcomes. In an analysis of Chile's electricity system, scholars found that optimizing across uncertain fuel prices lead to greater renewables and storage, and note that "failing to appropriately upgrade [capacity expansion] models may lead to a significant underestimation of [renewable] integration costs and risks, misleading relevant decisions in policy, regulation, [and] market design" [194].

As has been demonstrated through recent events, the status quo for energy consumption and production cannot be relied upon to continue indefinitely. The impact of recent price shocks has yet to be fully quantified, but early indications within the UK show that households had cut gas and electricity usage more than 10% heading into the 2022 winter season due surging costs [195]. In parallel, plug- in electric vehicle sales increased by 26% year-over-year in October 2022. The fragmented nature of the PV, domestic energy storage and EHP market makes it difficult to assess trends in the near-term but the 404% increase in wholesale gas prices and 346% in wholesale electrical prices from 2021 to 2022 [196] will inevitably drive consumers to seek renewable alternatives to their existing electrical and gas grid-fed supplies. Therefore, whilst renewables penetration studies can forecast uptake on the basis of demographic, geospatial and climatological factors, renewables uptake at the LV level is still ultimately subject to wider macroeconomic dependencies which can disrupt previous adoption trends.

To summarise, the limitations of static trial data coupled with underlying economic and behavioural assumptions required for penetration studies alongside macroeconomic dependencies present a need for overcoming these constraints. Trial data remains essential as a method of capturing population-level effects that cannot be robustly modelled through traditional methods such as physics-based buildings models. For example, a hi-fidelity model of a building plus heating system can be constructed to explore the relationship between heat and electrical demand, but this requires additional assumptions regarding occupant behaviour and local factors such as weather. Similarly, penetration studies are key for supporting the examination of feeder-specific impacts with respect to increased renewables penetration, but there remains the difficulty of validating what is a reasonable penetration level.

As a countermeasure to the uncertainty surrounding technology penetration, the magnitude and pattern of electrical heat load, a novel concept is proposed. This concept seeks to exploit the existing body of insights provided by generic trial data and augment it with the depth of locally specific insights obtainable from operational data extracted from the existing LV feeder monitoring infrastructure.

6.3 Concept

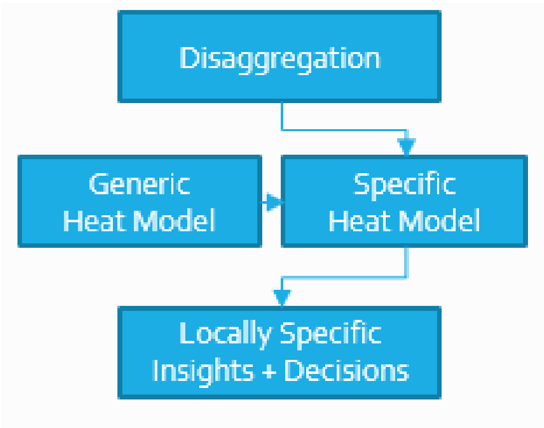


Figure 6-1 Unification Concept Overview

To overcome the limitations of demand models derived from trial data coupled with the limitations in renewables penetrations studies, a concept for drawing on the previously developed electrical heat disaggregation methodology combined with the generically derived electrical heat load models is proposed. Figure 6-1 provides a top-level view of how the existing concepts described previously in this work link together. Through the use of disaggregated electrical heat load from LV transformer data, a locally specific electrical heat load model that overcomes the temporal and spatial limitations of generic heat load can be derived. Due to the disaggregation methodology drawing on existing sensor outputs, there is no requirement for additional hardware monitoring for this implementation. Table 6-1 provides an overview of the pros and cons for trial versus operational data when aiming to predict electrical heat load on an LV network. Although not a full digital twin implementation, this work seeks to create a digital twin type relationship between electrical heat load and an LV feeder that could then feasibly be scaled to encompass all LV load types.

	Trial Data	**Operational Data**
Pros	Complete set of time series data Controlled data collection environment Electrical heat load specific measurements High sampling frequency	Temporally and spatially specific to target area Underlying penetration can be inferred
Cons	Need for translation to target area Temporal and spatial differential from target area No inferable penetration information for target area	No isolated electrical heat load measurement Low sampling frequency Data quality; sparse/incomplete data

Table 6-1 Overview of Pros and Cons for Trial versus Operational Data in Predictive Context for Electrical Heat Load

The top-level concept coupled with the previously developed work in Chapter 3 and Chapter 4 is shown simplistically in Figure 6-1. The physical entity represents the physical asset and it’s associated conditions; in this case a LV network transformer and the applied electrical load. As has been explored in previous chapters, this load is sensitive to various parameters such as time of day, time of year and weather. The load data is then fed to the processing stage. This is where disaggregation of the base LV transformer load occurs via the methodology presented in Chapter 5, allowing for the extraction of electrical heat load from non-heat load. This disaggregated electrical heat load can now be fed to the digital entity, which is a model representation of the LV feeder, transformer and associated loads. The generic electrical heat load model developed in Chapter 3 and 4 can now be supplemented with the extracted feeder-specific electrical heat load. In turn, this facilitates the modelling of outcomes beyond the conditions observed on the feeder. This can be supplemented with auxiliary data sources such as weather and supporting socioeconomic data.

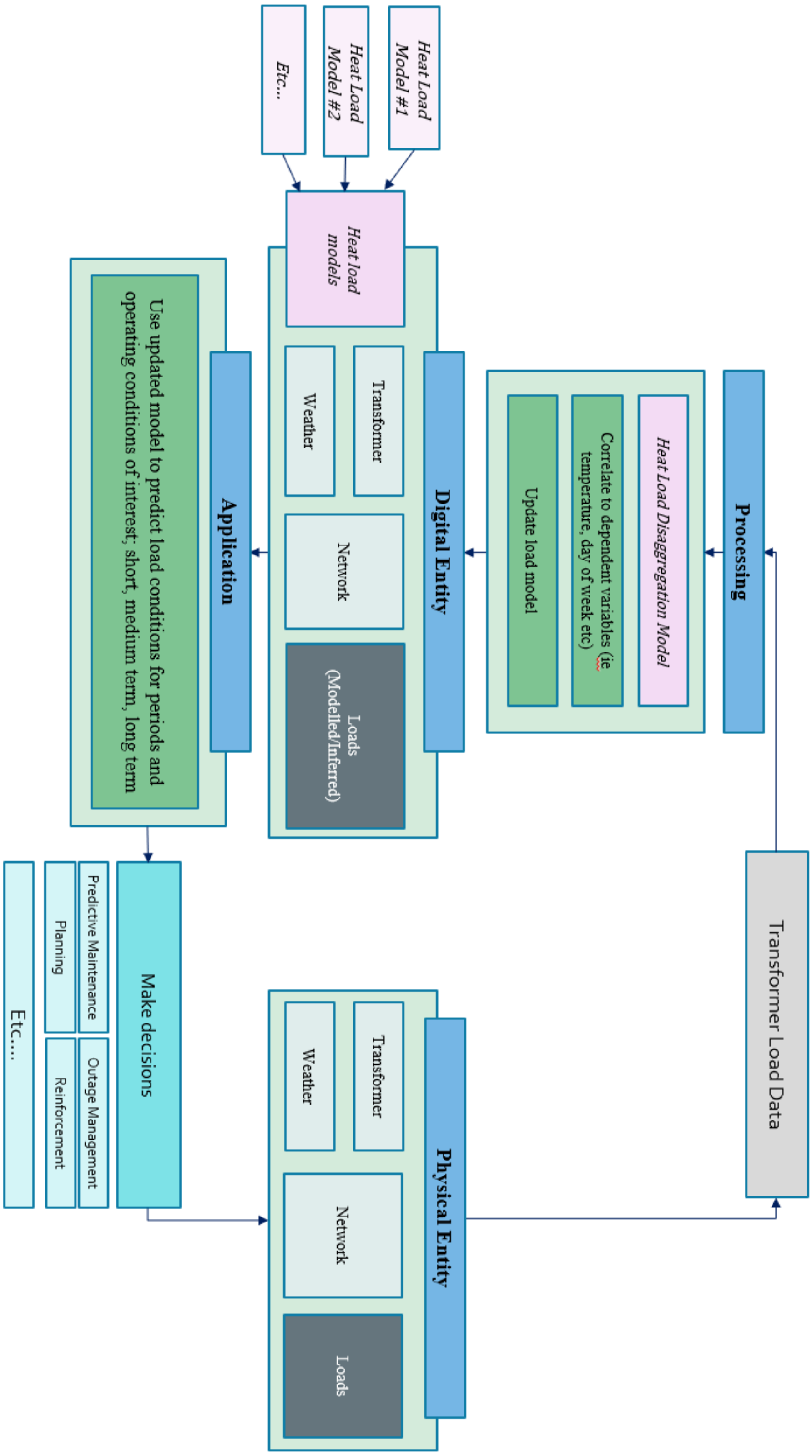


Figure 6-2 Detailed Unification of Electrical Heat Load Modelling and Disaggregation work

In an operational environment, captured operational data may not be as complete or sampled at the same high frequencies as trial data [8]. Furthermore, due to the need to disaggregate from LV transformer data, the difficulty of not having an isolated electrical heat load measurement must be offset. This supports the extension of predictions derived from disaggregated heat load beyond the operational range of the recorded measurements. This is of particular value when aiming to infer electrical heat load for worst case winter conditions, such as those experienced during winter of 2018 when several low temperature records were broken in quick succession [142].

6.4 Applications

The unification of generic models derived from trial data alongside locally specific models derived from more limited operational data present a range of application opportunities for DNO's as they face the facilitation of increased renewables penetration.

The changes in UK generation and load mix at the LV distribution network level necessitate an understanding of the specific electrical network impacts as a result of these changes. Whilst large-scale generation poses a simpler problem for characterisation and analysis, the distributed nature of small-scale load and generation at the LV network level presents a different problem. To date, analysis of future potential network impacts has been supported by models based on engineering principles supported by exemplar datasets where available. Both engineering assumptions and underlying data used for model construction stand to bias results, therefore this chapter has presented an alternative methodology that seeks to reduce these effects.

Feeder-specific load models present several application opportunities in both planning and operational type areas, as well as opening up opportunities for decision-making and analytical interactions with local stakeholders such as councils and commercial entities as well as individual citizens.

Practical Implementation for Distribution Network Operators

The methodologies developed in Chapters 3,4 and 5 outline standalone concepts that draw on static trial data or operational transformer data in order to predict electrical heat load. Chapter 7 combines this into a unified methodology that leverages the benefits of using existing trial data combined with real-time operational aggregated transformer load to provide locally specific insights. In the context of DNO's working towards greater integration of data-driven solutions for planning and operational tasks, this work contributes several benefits.

By exploiting information already embedded in transformer monitoring, the disaggregation techniques in Chapters 3 offer a way to estimate electrical heat load penetration on a feeder without the need for additional monitoring hardware. Given the scale of the electricity distribution network, solutions that minimise physical intervention in existing infrastructure provide are particularly attractive from an investment perspective. Solutions with low requirements for physical intervention enable DNO's to rapidly test out new methodologies with reduced risk to existing infrastructure, and then subsequently scale successful trials up to business as usual BAU as required.

The combined methodologies offer a solution for predicting electrical heat load that is directly linked to understandable parameters such as external air temperature, and equivalent annual gas demand. This has several benefits for usability in a commercial environment; in contrast to a black-box solution, the model outputs described have a clear link to physical model inputs and the inputs can be fully linked to the outputs. The transparency of the developed approaches therefore allow results to be sense checked or audited by non-expert users, increasing the maintainability and dependability of the model for use in future applications.

Finally, the works developed in Chapters 3 and 4 draw on contemporary electrical heat pump trial data combined with gas demand data. As has been discussed previously, these datasets are subject to becoming less representative with time as technology evolves, building efficiencies improve and household energy consumption evolves. A key strength of these models is their adaptability; the models developed are not restricted to being used with the existing trial datasets. Future datasets, as long as electrical heat load is captured at a minimum of one-hour resolution can be substituted in to refresh the model outputs without requiring any fundamental change in approach. Similarly, any daily average temperature series can be used as long as it is relevant to the geographic area being studied. This enables model outputs to be periodically refreshed as new representative data is forthcoming.

Planning horizons for distribution networks can span decades, and techniques that remain explainable in the midst of changing conditions are key for DNO's seeking to optimise investment in the face of an ever-evolving political, technological and regulatory landscape.

As standalone models, the work in previous chapters also offer low computation times alongside their maintainability. Electrical heat load for a group of 100 customers on an LV feeder can be modelled with less than 10 minutes of computation time; this could be further reduced with appropriate refactoring; this is less than the 30-minute time settlement interval used by energy markets. As part of a larger integrated system, further computation time would have to be allowed to permit for the transfer of data, communications and any further new system interfaces such as a presentation or visualisation layer at the decision-making interface.

A conceptual model pipeline would vary depending on the specific architecture and constraints of existing systems, but generally would consist of the data collection, processing and decision making layers presented in Figure 6-2. A practical implementation would utilise the existing monitoring and data handling infrastructure embedded within an LV substation.

The combined disaggregation and electrical head load prediction model would be hosted remotely; with the ready availability of cloud computing, an automated pipeline that ingested aggregated transformer load data could be hosted on a remote Amazon Web Services (AWS) instance. Compared to an in-house IT solution, the implementation could then benefit from several cloud-specific advantages such as auto-scaling, where the hosted instance can be automatically scaled up or down based on demand, and elastic infrastructure, where computing resources can be adjusted with time to optimise cost versus performance. This architecture also allows for the ingestion of parallel data streams from multiple LV substations simultaneously, facilitating insights at a regional or licence-area specific level.

The decision-making layer and how this interfaces with model outputs would then be tailored to the specific use-case and needs of a DNO. To support planning type decision-making, automated reports could be generated over monthly or longer time horizons to provide an up-to-date view on the adoption of EHP across households in a licence area. Alternatively, a digital twin-type model that reflected the existing state of a network could be offered alongside the capability to turn-up and turn down parameters such as penetration levels and weather conditions to understand how a network segment might react under scenarios of more extreme loading.

On shorter time-scales, decision making tools could be offered for network stakeholders making operational decisions. Forecasts for electrical heat load in areas of interest could be updated on a rolling basis as weather forecasts are correspondingly updated by forecasters. Ten-day weather forecasts are cited as only being right around 50% of the time, whereas a five-day forecast can accurately predict the weather in around 90% of cases [197]. Increasing weather forecast accuracy over shorter time horizons translates into increased confidence intervals for electrical heat load; this can enable network operators to anticipate time periods of particularly high or low network utilisation to correspondingly optimise their short-term decision making.

6.5 Conclusions

This chapter has presented an integrated concept for extracting a locally specific electrical heat load model from LV transformer data, supplemented by generic models derived from historic trial datasets. This provides an interface between real world data collection and existing predictive models, where the limitations of standalone predictive models are overcome with live data.

To effectively utilize the full potential of the digital twin type technology in the power system, a holistic approach is required to address various challenges such as modelling, data management, storage, computational requirements, and scalability [127]. Even though high-performance computing facilities and emerging technologies such as cloud computing could serve as a stepping-stone to deal with most of these challenges, the challenges related to modelling and data management require more than engineering skills to solve [198]. Furthermore, efficiently balancing the trade-off between the accuracy of predictions by digital twins and optimizing computational complexity required for various types of models/data will be challenging [199].

Decarbonisation strategy comes from top level decisions in government but the success of UK decarbonisation depends on ability to be responsive and flexible in adapting implementations at the local level. Developed solutions must be sufficiently adaptable to account for the inevitable step-changes in energy usage patterns as stakeholders drive towards Net Zero. In the past, taking a one-size-fits-all approach to infrastructure development has often resulted in poor outcomes for local residents and users. The specific needs and challenges of different communities can vary enormously.

In an environment where DNO's are increasingly looking to exploit network data for operational and planning type tasks, this chapter presents a concept for linking engineering models with generic trial data and feeder specific operational data.

Chapter 7

Conclusions and Further Work

This thesis has addressed some aspects of the difficulty of modelling electrical heat load in a LV distribution network context, which is characterised by low observability, low availability of data and high levels of uncertainty with respect to how uptake of the technology will proceed over the medium to long term. Building on previous works which focused on modelling EHP impacts at operational extremes using standalone trial data, such as a worst-case winter day case, this work has demonstrated methodologies for supplementing limited and aging trial data with complementary weather and geospatial datasets in order to broaden the scope of network studies and maximise the value of potential insights. Additionally, the future possibility of model integration with live operational data to fill the gap between trial data and real-world needs has been explored.

The chapters presented in this work form a contribution to de-risk accelerated adoption of EHP's at the distribution network level. EHP technology forms a fundamental component of reducing UK domestic heating dependency on fossil fuels. However, the integration of EHP to existing networks presents a significant planning and operational challenge for DNO's and future distribution system operators' (DSOs) due to a combination of factors relating to the technology itself, as well as the context of the intended application. The significance of EHP power and energy characteristics in comparison with existing household usage, combined with their seasonal variability, their sensitivity to geospatially variable parameters such as building construction and householder routines. This is further compounded by the level of difficulty of intervention for existing and future housing stock. As the integration of LV-connected renewable technology gains momentum in the coming years and DNO's seek to balance cost-driven commercial decisions with technically-driven operational decisions, sufficiently understanding the energy mix on a feeder will be key to optimising future investment and operational decisions.

7.1 Outcomes of Research

The main observations and results from the work presented in this thesis are summarised in this section. Electrical heat load contributed by increasing domestic heat pump penetration at the LV distribution network level is a function of residential thermal comfort levels and climatological conditions as well as physical building characteristics. The energy and power characteristics of domestic heat pumps combined with their temperature sensitivity will alter conventional LV load patterns and necessitates sufficient understanding for LV network operators to minimise risk to network assets and security of supply.

Weather Localisation of Electrical Heat Load for Distribution Networks

As a response to the limitations of building physics-based models and pure aggregated trial-data for quantifying potential LV network loads, this work has developed a methodology for scaling existing trial data sensitive to geospatially variable parameters.

In order to offer insights beyond the operational extremes presented in existing studies through aggregation of existing trial data, a methodology for predicting electrical heat load sensitive to local temperature conditions was developed. The RHPP and LCL EHP datasets were paired with corresponding temperature data in order to derive an electrical heat load versus temperature relationship. The most direct dependency was identified between daily average temperature (°C) and normalised daily demand. By expressing both temperature and demand at a daily resolution, the inherent variability due to diurnal temperature variation and heat pump cycling could be minimised. Through demand normalisation, the range of customer sizes in the trial could be observed across a common scale. The outcome of this work was to provide a model for electrical heat pump load that was sensitive to both the entire range of operational temperatures (as opposed to operational extremes) and number of customers. A key capability is the ability to model electrical heat load versus low numbers of customers, as opposed to high numbers of customer aggregations. This facilitates examination of increased EHP penetration effects for LV customer scales.

This model is constructed on the assumption that daily average external air temperature is the primary factor in electrical heat load demanded by a household. Linking hourly electrical heat load shapes to a single daily average external air temperature will not capture the variations or fluctuations of electrical heat load driven by normal temperature variation throughout a day. As a measure of purely external air temperature, it does not take into account other weather conditions such as snow, ice or wind and their influence on electrical heat load. Additionally, this work is dependent on correlating the Central England temperature series to RHPP customer loads – this temperature series will be on average representative of customers local weather conditions, but locally specific extremes may not be captured using this methodology. Future work that is not constrained by anonymised customer locations could develop a more refined relationship between electrical heat load and variation in local weather conditions.

Scale Localisation of Electrical Heat Load for Distribution Networks

A further development was to overcome the scale limitation of the previous chapter by developing a methodology for providing geospatially sensitive magnitude scaling. This was performed through the unification of geospatially linked annual gas demand data to inform the scaling of the normalised magnitudes output by the previously developed model. Three different heat-type datasets (gas, electric and direct heat) were used in order to test the relationship between annual and daily demand prior to application of the methodology in a case study.

The presented case studies demonstrate the variability in EHP impact sensitive to the range of existing gas demands in the UK. The ADMD case study demonstrates the variability in ADMD versus a range of plausible COP values, demonstrating the sensitivity of network impacts to geospatial influences and COP. A more extensive case study versus penetration is performed, demonstrating the variability in feeder endpoint voltage versus various penetrations and geospatially-inferred electrical heat demands. This contribution therefore can be used to support identification and assessment of individual LV network feeders at risk due to elevated penetrations of electrical heat pumps.

As has been discussed previously, this methodology makes the assumption that annual average gas demand for a postcode can be converted to heat and subsequently electrical heat load through the use of simple linear conversion efficiencies. This model therefore assumes that the heat demand required by a household is technology-agnostic, and is not influenced by whether the system is fossil-fuel fired or an electric heat pump supplied system. There is the risk that as customers shift to new heating types, any corresponding energy and cost savings translate into greater energy usage, resulting in a rebound effect and eroding the benefits of improved efficiency. Due to the present market penetration of heat pump technology in the UK this is a difficult phenomenon to capture, but as an increasing amount of households convert from fossil-fuel based heating systems to HP based systems, there is the opportunity to examine how the change in heat source impacts the final heat demand of a household.

LV Network Heterogeneity and Implications for Renewables Modelling

This work has examined the heterogeneity present at the LV network level and the implications for electrical heat modelling, as well as low carbon technology modelling in a wider context. The transmission scale energy network is characterised by a comparably small number of high value, well characterised and well monitored assets. In contrast, the distribution network is responsible for facilitating the electrical supply for every domestic and commercial user in the UK. Electrical load provision is a function of human behaviour and needs; in the most general terms this translates to higher energy usage during daylight hours where human activity is most concentrated. However, at more granular geographic scales the unique constraints imposed by a specific geographic area stands to influence energy usage patterns and therefore electrical load imposed on an LV network. These parameters include human behaviour related to social and economic demographics, as well as physical effects such as weather, building construction and type. Chapter 4 presented the annual gas usage variation inherent at postcode level within the UK. From here, a novel methodology was constructed to demonstrate the same variability for equivalent electrical heat load in the case of increased heat pump penetration on a feeder. The variability in ADMD given the annual electrical heat load magnitude was then modelled and tested for several test cases on an LV feeder.

This contributes a process for inferring geospatially specific heat demand, and therefore electrical heat demand through the use of up-to-date postcode aggregated gas demand. This therefore provides a means of locally scaling electrical heat load, where national averages are presently used.

Similarly, whilst the bulk electrical heat load installed in properties on an LV feeder may vary geographically, localised weather effects also stand to drive variations in electrical heat load. The work in Chapter 3 developed a methodology for modelling electrical heat load with respect to temperature, as opposed to the worst-case maximums that are typically used in existing works.

Limitations of Trial Data for LV Network Modelling

A unifying aspect of this work is the need to overcome the limitations of trial data in an LV networks context for EHP modelling. Electrical heat pump modelling is conventionally performed through two primary approaches: the physics-based approach, and the data-driven approach. The physics-based approach entails detailed physical parameterisation of the heating system, allowing for a transparent relationship between EHP activity and corresponding load imposed on the LV network. However, whilst the detailed variables can be defined, their specific values necessitate some level of assumption or abstraction due to the inherent variability in UK housing stock and occupant thermal routines. In order to bypass this, data-driven approaches which draw on trial data are used as an alternative. Trial data, which captures the actual load of domestic EHP's, reflecting true time of use activity and sensitivity to geospatially variable parameters. However, due to the slow time scales involved with trials and restricted sample sizes, trial data in and of itself does not present a complete solution.

Presently there is a heavy dependency on trial data to inform the magnitude and time of use characteristics of LV-connected electrical heat pumps, and their corresponding impacts on LV network assets. In addition to heat pumps, this is a key issue for EV integration, as well as to a lesser extent rooftop solar and small-scale distributed generation.

This is in part driven by the scale of the distribution network; with 27.8 million households in the UK it is naturally not feasible to characterise the power consumption of individual households and how they might alter with low-carbon technology integration. Alongside this, household smart meter data is not presently available to DNO's due to regulatory restrictions. Therefore, representative samples obtained through controlled trials offer insight into potential network impacts through increased renewables penetrations. As of 2023, the primary UK electrical heat pump dataset is six years old. This therefore means that the reference datasets used to model domestic electrical heat load may be dated in terms of the technology and consumer usage.

Future distribution network operation will become more fundamentally proportional to a wide range of load and generation types, beyond conventional household energy usage. Therefore, as distribution networks proceed through the earliest stages of renewables integration to a more mature footing, corresponding methodologies for supporting the understanding of future LV network loads must be developed to support this.

EHP Operation Outside of Trial Data Temperature Ranges: Extreme Cold

As has been highlighted previously in Chapter 3, the methodology developed in this work is inherently dependent on the raw trial data used to construct the relationship between electrical demand and outside air temperature. The sampled temperatures present a roughly linear relationship between the electrical load of an EHP and the outside air temperature from roughly 15 °C down to 0°C as shown in Figure 3-3. Additionally, due to the anonymisation of individual customers within their respective datasets, it is not possible to reliably identify customers EHP that are operating at cold extremes as the model only infers average temperature from the Central England weather series, as specific customer location and therefore specific customer weather is not known.

Therefore, the developed method provides limited insight into the relationship between EHP electrical load and outside air temperature for operating regions beyond the 0°C daily average temperature already modelled.

[200] illustrates the relationship between COP and outdoor air temperature for a range of various commercially available air-source heat pumps. Within the 0°C to 15 °C operational band, device COP ranges from approximately 2.5 to 4 – roughly in line with the winter COP assumed in Chapter 4. However, beyond 0°C the COP is subject to further reduction, approaching as low as 1.6 for one brand of device.

Figure 4-15 in Chapter 4 has demonstrated the relationship between COP and calculated ADMD (kW), with increased COP imposing an increase in calculated ADMD for a feeder. For a EHP capable of a 16kW heat output, a change in COP from 2.5 to 1.5 would result in an increase in electrical demand from 6.4kW to 10.67kW to meet the same target heat output – over a 60% increase.

As EHP's are intended to replace conventional fossil fuel fired systems as the primary heat source in modern households, their performance at cold extremes is a point of critical analysis. Future LV networks must be designed to accommodate not only increased uptake of electrified low-carbon heating, but also the risks imposed by operating these devices under worst-case cold conditions.

Disaggregation of Electrical Heat Load for LV Networks

As an alternative to trial data, the disaggregation of electrical heat load from aggregated load data at the point of the LV transformer was demonstrated in Chapter 6. This was presented as a methodology that could circumvent some of the limitations surrounding age and applicability of trial data, by using trial data for characterisation of the physical relationship and using feeder specific data to refine final estimations of electrical heat load for various cases. This mitigates the localisation issues with trial data, providing a feeder-specific quantification of electrical heat load. However, the common seasonal phase of heat and non-heat load on a feeder necessitates alternative methods for performing reliable disaggregation.

Through the use of EDRP smart meter and RHPP trial data, this disaggregation process emulates feeders that have a mix of conventional household non-heating electrical load and the addition of electrical heat load. Data was collected for the EDRP study between 2007 and 2010 [158], whereas the RHPP data collection concluded in 2015 [8]. Since then, several changes have evolved in how households consume and use energy. The number of EV's in the UK has grown more than ten-fold since 2015 to 2023 [201], impacting the energy consumption and usage patterns of households that are able to make use of home charging. Similarly, for rooftop solar, industry body MCS recorded a cumulative total of 640,883 rooftop installations in 2015, which now stands at 1,471,106 as of 2024 [45]. The Covid-19 pandemic saw remote working in the UK rise from 5% in 2019 to 38% in June 2020 [202]. Whilst these levels have reduced from their pandemic peak, as of 2023 some 25% and 40% of working adults in the UK report some level of home working [203]. This situation is still evolving and therefore future work attempting to disaggregate electrical heat load from electrical non-heat load should be sensitive to these changes.

Integration of Operational and Trial Data

The methodologies developed in Chapters 3, 4 and 5 were tied together in a concept that unified online operational data that provided locally specific insights into electrical heat load, alongside generic heat load models developed from trial data. The approach here therefore leverages multiple sources of data in order to overcome the limitations of standalone operational and trial datasets.

The individual methodologies developed in Chapters 3, 4 and 5 for predicting electrical heat load are all fundamentally dependent on the trial data [2] [8] [158] used in order to inform load time of use, energy and power characteristics. Whilst electrical heat load usage patterns will remain inherently sensitive to external air temperature and prevailing weather conditions, the integration of these methodologies in a real-time system presents many opportunities for further work. A system drawing on real-time transformer load data will be subject to more variability than the pre-screened and pre-selected customer data collected in a controlled and designed trial environment. Real world feeders may result in certain customer groups with particularly concentrated usage patterns, featuring lower levels of diversity compared to the typical levels obtained from the trial data derived results. Data quality issues, such as communications failures, or faulty sensors could influence model outputs and therefore would need to be handled appropriately without compromising model quality or utility.

However, these kinds of issues are typical when translating concepts from theoretical studies to real-world implementations. Therefore, the specific effects to be compensated for would dependent on the requirements of end-user and the existing constraints of their system.

7.2 Future Work

This work has demonstrated methodologies that further develop electrical heat load predictions in the presence of incomplete data and knowledge. However, as discussed in Chapter 1, research is still very much constrained by the limitations of trial data when attempting to infer future LV network conditions. Whilst trial data is suitable for making average or general insights for network impacts, the inherent heterogeneity of the power distribution network necessitates the fact that trial data does not capture all of the inherent variability present at LV level. Potential future work that builds on the existing concepts already explored is described below.

Cross-referencing with data from Electrification of Heat Demonstration BEIS Project

The BEIS Electrification of Heat Demonstration project, managed by Energy Systems Catapult, is currently underway as of 2022. This program is recruiting 750 households for the installation and ongoing monitoring of heat pumps for domestic heating, across a representative range of housing archetypes and social groups. This is a study very similar in size and scope to the previous BEIS program, which monitored domestic heat pumps installed via the Renewable Heat Premium Payment scheme. However, as previously discussed in Chapter 3, the data collected for the RHPP study was originally collected from 2013 up to 2015. This means that data collected from the RHPP study inherently features almost ten years' worth of lag between the present day and existing householder routines, building standards as well as heat pump technology.

The renewal of UK-based domestic heat pump trial data therefore presents an opportunity to update existing models and cross examine any outputs from the RHPP-derived findings versus the more up to date datasets.

Off-gas correlation pairs with gas postcodes

The work performed in this thesis has focused on the LV-network level effects of grid-connected households transitioning from gas-fired domestic heating to EHP-supplied heating. However, a specific difficulty is presented by the modelling of off-gas postcodes. This is characterised by the following challenges:

- Off-gas households do not represent the typical UK household and therefore deviate from the mean in terms of building construction and type; the majority of off-gas postcode are present in remote rural localities in Scotland and Wales.

- Existing RHPP study approximates the only mean of UK households and is not representative of edge cases such as rural households.
- The lack of gas-grid connection for off-gas households further reduces the data available as no metering is available to draw on for understanding household consumption.

These difficulties are offset by the fact that off-gas households present good candidates for EHP installation. Off-gas grid households are reliant on some of the highest-carbon heating fuels, including oil and coal [204] and retrofitting existing households to utilise EHPs presents an opportunity to reduce the carbon footprint of these households. Under the UK Government Heat and Buildings Strategy EHP installation in off-gas homes is categorised as a low-regrets solution [38], whilst a BEIS survey found that only 9% of installers reported issues with building stock of off-gas-grid homes being a barrier to further UK heat pump deployment [205].

Off-gas postcodes pose a challenge due to comparative lack of heating routines and available data. An opportunity exists here for the correlation of unmetered homes with metered homes to investigate potential off-gas impacts and better quantify electrical network effects for rural feeders with increased electrical heat pump penetration.

Multi-LCT modelling

Chapters 3, 4 and 5 have focused on the effects of increased EHP penetration at the LV level. However, the future power distribution network will incorporate a mix of electrical low-carbon technologies, including electric heat pumps, electric vehicles of various sizes as well as distributed generation such as rooftop solar, small-scale wind, energy storage and larger LV-connected installations. Sufficiently understanding future network loads sensitive to magnitude, time of use and specific sensitivities of each LCT-type will be key. Furthermore, as DNO's become more sophisticated there will be a natural transition from using static trial data to provide indicative loads and more active exploitation of operational data in order to drive decision making.

The localisation capabilities offered by the developed methodologies are of particular interest for local area energy planning (LAEP) activities. This is a relatively new process designed to empower localities to achieve emissions reductions tailored to their unique geography, physical infrastructure, natural resources, political and social landscape [206].

An Innovate UK study [207] compared baseline deployment of two alternative scenarios that met the CCC's Sixth Carbon Budget [37]; a 'place-agnostic' deployment, where low carbon measures were adopted uniformly across areas, and a 'place-specific' deployment, where each city-region was enabled to adopt the most socially cost-effective low-carbon measures. The place-specific scenario was modelled with requiring less than a third of the investment required by the place-agnostic scenario, whilst resulting in an additional £400bn of social benefits [207].

This represents an extremely powerful opportunity to achieve decarbonisation goals in a way that maximally targets the local needs of an area. Targeted action to insulate homes in poor housing stock could translate into warmer homes, improved health outcomes and social benefits, whereas the same action in a more affluent area may not result in the same returns due to an already elevated baseline. Similarly, homes in wealthy areas of rural Surrey may present radically different decarbonisation opportunities versus a rural area in the Scottish Highlands.

The developed models have been constructed with sensitivity to external air temperature, using the Central England temperature series, but translatable to any Met Office temperature series. Similarly, the modelled electrical heat load derived from postcode-specific annual gas demand in Chapter 4 is adaptable to any postcode or area-specific gas demand. Therefore, when paired with local weather data and existing knowledge of local gas demand, a locally specific electrical heat load can be modelled for a range of penetration and existing heat demand assumptions. Whilst subject to the constraints outlined earlier in this section, these methodologies create an opportunity for low-cost and rapid assessment of electrical heat load impact for local area energy planners. Combined with an appropriate cost modelling methodology and existing approaches for modelling other LCTs, planners could work with network operators to understand where investment in low-carbon heat solutions such as heat pumps could be targeted to maximise social gains for local communities whilst also achieving tangible emissions reductions.

7.3 Final Thoughts

The negative impacts of climate change and its wider effects have exceeded scientific expectations in recent years, with unprecedented extreme weather events occurring globally in 2022 alone. In August, areas in Pakistan received 784% more rainfall than the monthly average, contributing to the worst flooding in the country's history and estimated economic losses of over $40 billion as well as untold damage to human life and communities. The 2022 summer heatwaves across Europe resulted in the worst drought conditions for 500 years, with the months of June, July and August measuring as the warmest on record for the continent by a substantial margin, breaking the previous record set the previous summer of 2021.

Colder weather brings its own difficulties, with the UK and Europe facing all-time-high wholesale energy prices due to supply-side disruption as the continent headed into the 2022/2023 winter season. The gas-dependency of UK households for space heating places additional cost of living pressures on consumers and energy companies at a time of already elevated economic difficulties.

Due to climatic, political, and economic factors, the balance between the three dimensions of the energy trilemma – security, affordability – has come under strain in the aftermath of the

Covid-19 pandemic. If not managed effectively, the crisis can compromise the pursuit of overarching net-zero emissions targets [208]. However, this also presents an opportunity to reassess current strategies, identify areas for improvement, and implement new approaches that can more effectively meet the goal of achieving net-zero emissions and preservation of the planet for future generations.

Chapter 8 Appendix

#	Temperature (°C)	Mean (μ)	Std (σ)
1	-2	0.1	0.002
2	-1	0.6	0.042
3	0	0.57	0.042
4	1	0.58	0.044
5	2	0.54	0.04
6	3	0.5	0.04
7	4	0.52	0.04
8	5	0.48	0.036
9	6	0.41	0.034
10	7	0.35	0.034
11	8	0.32	0.032
12	9	0.27	0.03
13	10	0.24	0.028
14	11	0.19	0.024
15	12	0.16	0.022
16	13	0.11	0.016
17	14	0.11	0.016
18	15	0.09	0.014
19	16	0.08	0.012
20	17	0.07	0.012
21	18	0.06	0.01
22	19	0	0

Table 8-1 Parameters used for (2), (3) in Chapter 3

Chapter 9 References

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