

**ENERGY DEMAND MODELLING
AND DEMAND-SIDE MANAGEMENT
WITH DETAILED REPRESENTATIONS
OF CONSUMER ACTIVITIES AND
BEHAVIOURS**

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To my parents

Declaration

I hereby declare that the entire research presented in the thesis is my own and the uses of material from other sources have been appropriately referenced.

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Abstract

Energy demand modelling and demand-side management (DSM) have been studied for years to accurately simulate energy consumption and explore energy-saving potentials. Recent research in the residential sector has further studied the impacts of consumer-related factors and electric vehicles (EV) on the performance of DSM. This thesis aims to improve energy demand modelling and DSM with detailed representations of consumer activities and behaviours, including four interrelated studies: (a) Design a framework to generate coordinated indoor residential loads and EV charging loads, integrating the connection between indoor and outdoor activities; (b) Test machine learning models for load profile generation, with novel features included to consider various influential demand factors; (c) Build a hybrid DSM optimisation model to integrate the connection between indoor and outdoor activities, as well as factors that influence demand, wherein the bias in the potential for improvement of DSM is additionally explored; (d) Design Stated Preference (SP) surveys and choice models to study consumers' activity adaptation in DSM with a consideration of various influential factors.

This thesis offers four key contributions with regards to concept, data, methodology and application respectively: (a) Demonstrate the significance of three novel concepts in energy demand modelling and DSM, including the connection between indoor and outdoor activities, the nonlinear relationship between consumer activities and electricity consumption and various influential factors on consumer activity adaptations; (b) Capture new evidence on detailed activity profiles and the changes to consumer activity patterns in response to energy pricing policies through analysing multiple datasets and the pioneering application of SP survey in this domain; (c) Provide practical guidelines in building energy demand models and DSM that incorporate the three novel concepts; (d) Support policy-making through the application of designed frameworks and models in the impact analysis of EVs, the assessment of DSM, as well as time of use tariffs.

Extended Abstract

Energy demand modelling and demand-side management (DSM) have been studied for years to accurately simulate energy consumption and explore energy-saving potential. Short-term bottom-up energy demand models aim to estimate daily electricity consumption profiles, also called load profiles, to facilitate the management and operation of electricity networks and power plants. DSM is the energy management technique that is used to modify the load pattern of the consumer (Kanakadhurga & Prabakaran, 2022) with the main objectives being to maintain the supply-demand balance and improve both economic viability and energy efficiency.

Recent research on energy demand modelling and DSM in the residential sector has further studied the impacts of consumer activities and behaviours, as well as electric vehicles (EV). Consumer-related effects are the key factors in driving electricity consumption, reshaping load profiles and determining the performance of DSM. However, these factors are often oversimplified or overlooked. Firstly, most research in energy demand modelling and DSM is based on indoor activities and travel patterns drawn from different contexts due to the challenges of accessing real-world data. This approach neglects the connections between indoor and travel activities. Secondly, linear relationships between activity types and energy consumption are usually established. However, the energy consumption of consumer activities is also influenced by other factors, such as the timing of activities and the interaction between simultaneous activities. Additionally, machine learning (ML) algorithms are rarely employed to generate residential load profiles. Thirdly, DSM inherits the bias in the energy demand modelling and fails to fully capture the impact of consumer activities, which may result in a biased and inaccurate assessment of DSM policies. Lastly, consumers' adaptation of household activities in response to DSM policies is usually assumed to be rational, driven by the desire to reduce monetary cost and restricted by simple ranges of activity start times. However, additional factors such as electricity prices and socio-demographics can play important roles in these behaviours.

This thesis aims to address the gaps discussed above and improve energy demand modelling as well as DSM with detailed representations of consumer activities and behaviours. Four specific objectives are proposed and achieved through four interrelated studies.

Objective A: Introduce the connection between consumer indoor activities and travel activities in load profile generation models. The first objective is achieved by designing a load profile generation framework that consists of two models that generate coordinated indoor loads and EV charging loads respectively for the same households. The key inputs are activity-to-power conversion factors and cohesive activity profiles within which indoor activity profiles and travel pattern profiles belong to the same individual and are therefore consistent with each other. Through this approach, the connection between indoor activities and travel patterns is retained. The impacts of generated EV charging loads on meter-recorded household indoor loads are analysed across three charging scenarios. Additionally, the generated indoor loads are validated against the same meter-recorded household indoor loads.

Objective B: Assess different methods and develop guidelines and recommendations for ML-based load profile models. To achieve the second objective, this thesis designs three groups of test scenarios and compares the performance of six types of ML algorithms in a multi-household residential context. Specifically, three groups of test scenarios include eight sets of influential features, four different widths of historical time windows, and two train-test splits. The six types of ML algorithms include Support Vector Regression, Artificial Neural Network, Long Short-Term Memory, Light Gradient Boosting Machine, Random Forest and K-Nearest Neighbours. Additionally, a novel feature “TimeCredit” is designed to capture the impacts and the interactions of simultaneous activities.

Objective C: Design a hybrid DSM model that considers consumer activities and interactions between them. In the chapter addressing the third objective, a hybrid DSM optimisation model is designed to incorporate the framework from Objective A and the best-performing models from Objective B. Therefore, the cohesive activity profiles, as well as multiple factors that influence demand, such as activity start times and the interaction between activities are considered. In addition, the potential bias arising from the neglect of the connection between travel activities and indoor activities is explored by testing the results of observed and simulated activity profiles.

Objective D: Generate new evidence and models that help us to better understand consumer behaviour in the context of DSM. This thesis introduces discrete choice models to study the influential factors in consumers’ adaptation of activities in DSM to

achieve the fourth objective. A stated preference (SP) survey, DSM-SP, is conducted to collect data on activity adaption in response to time of use (ToU) tariffs in hypothetical situations. Consequently, mixed logit discrete choice models are estimated for six common household activities, including cooking hot meals, boiling drinking water, showering, using a washing machine, working and leisure, and two measures of value change, i.e., saving and payment. In addition, case studies are designed where the estimated choice models are used to predict consumer responses to different ToU price levels and study the distributional impacts.

This thesis offers four key contributions particularly in concept, data, methodology and application respectively: (a) Demonstrate the significance of three novel concepts in energy demand modelling and DSM. Neglecting the connection between indoor and travel activities will result in bias in energy demand modelling and DSM. The nonlinear relationship between household activities and electricity consumption should be considered with additional influential factors such as electricity prices, activity patterns and socio-demographics, instead of solely relying on activity occurrence and constant conversion factors. Similarly, these influential factors play a role in consumers' activity adaptation in response to ToU tariffs. (b) Capture new evidence on detailed activity profiles and changes to consumer activity patterns in response to energy pricing policies. To the best of my knowledge, the DSM-SP survey is the only application of SP methods in studying specific activity adaptation in DSM research to date. (c) Provide practical guidelines in building energy demand models and DSM that incorporate three novel concepts in this PhD research. The results show that short-term meter-related features are sufficient to predict electricity consumption, while survey-related features can make the model robust against sudden load variations. (d) Support policy-making through the application of the designed frameworks and models in the impact analysis of EV, the assessment of DSM and the estimation of ToU tariff benefits. For example, the distribution of peak and off-peak hours in ToU tariffs should be designed carefully to avoid the contradiction between minimising cost and peak-to-average-ratio. The estimated choice models indicate that participants are sensitive to the amounts they are charged but not as sensitive to savings arising from adapting activity schedules. Therefore, when promoting ToU tariffs, it may be more effective to emphasize the comparison between electricity bills before and after switching to ToU tariffs, rather than solely focusing on savings.

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Chapter 1

INTRODUCTION

1.1 Background and motivation

The challenges of energy conservation, climate change and energy security have motivated intensive research interest in energy demand modelling and demand-side management (DSM). These strategies and research hold the potential to improve energy efficiency, offering benefits to both energy producers and consumers. On the generation side, rather than unrestricted infrastructure expansion, energy producers are now focusing on managing demand through incentives and price signals to address the increasing demand (Pawlak, Imani & Sivakumar, 2021; Lund et al., 2015). Moreover, the adoption of renewable energy, while reducing the reliance on fossil fuels, has increased the variability of the electricity network due to its intermittent nature and widely dispersed geographical location (Pallonetto et al., 2019). On the demand side, financial, environmental and social motivations drive consumers' desire to understand and control electricity consumption (Parrish et al., 2020). In addition, the promotion of electric vehicles (EVs) as alternatives to conventional fuel cars may lead to large energy load variations, high peak demand and power quality degradation due to uncontrolled charging and discharging behaviours (Al-Ogaili et al., 2019; Zou et al., 2023). Thus, given these motivations and challenges, this PhD research focuses on short-term energy demand modelling and DSM as important tools for improving electricity network management and energy efficiency.

The residential sector has great potential in reducing energy consumption. In 2021, the residential sector consumed the largest part of total electricity sold to ultimate consumers in the US, at about 38.9% (IEA, 2022b). In 2020, the household sector constituted about 28% of the final energy consumption of electricity in the EU (Eurostat, 2020) and the domestic sector was responsible for approximately 32.5% of the total final energy consumption in the UK (Department for Business, Energy & Industrial Strategy, 2022). However, the diversity in household electricity-powered devices, consumer activities and behaviours increases the difficulty in predicting and modelling

residential energy consumption (Proedrou, 2021). Furthermore, the total number of EVs on roads in 2021 globally reached about 16.5 million, which tripled the number in 2018. As part of this huge increase, 6.6 million battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) were sold in 2021 (IEA, 2022a). These two types of EVs draw electricity from the grid and thus generate substantial charging demand. The surging charging demand accompanying the increasing number of private EVs therefore imposes further challenges in residential energy management. Therefore, energy demand modelling and DSM require more research efforts in the residential sectors, particularly in relation to EVs, and the diversity of human activities and behaviours.

1.1.1 Energy demand modelling

The need to model energy demand stems from several reasons. Accurate forecasts of energy demand are essential for power system operators to strategically plan power generation, integrate renewable energy and ensure grid security. Building owners use building energy simulation models to assess and enhance energy efficiency. Additionally, the electricity market and DSM policies rely on energy demand models to design appropriate price signals and incentives to balance supply and demand. Furthermore, consumers also show interest in understanding their energy consumption patterns due to rising electricity costs and the increasing awareness of the importance of energy conservation. To meet the above needs in the residential sector and connect human activities with electricity consumption, this PhD research focuses on load profile models in energy demand modelling. This type of model is defined as a system that can reproduce the combined electricity consumption of all the electricity-powered devices in a number of private residences (Proedrou, 2021).

Three terms, namely energy, demand and load, are often used interchangeably in the literature on energy demand modelling. The subtle differences between them necessitate clarification. Generally, energy encompasses electricity, gas and hot water. In energy demand models, however, it specifically refers to electricity unless otherwise stated. With this premise, energy (measured in kWh) implies the electricity used by appliances or delivered by the grid. Demand (measured in kW) is the amount of electricity required over time to meet a certain requirement, such as providing lighting in a building. On the other hand, the term load has multiple meanings in the literature,

such as active power (measured in kW) (Chitsaz et al., 2015), apparent power (measured in kVA) (Xu, Wang & Tang, 2019) or energy (measured in kWh) (Alani & Osunmakinde, 2017). In load forecasting, the load usually means demand (measured in kW) or energy (measured in kWh) (Hong, 2014). For this PhD research, the electricity required to undertake activities and charge EVs is modelled and managed. Therefore, load refers to the energy (measured in kWh) and these two terms are used interchangeably.

Despite extensive research and numerous applications, choosing the appropriate method to model electricity consumption remains an open research question in terms of the selection of modelling method, feature engineering for data-driven methods, application contexts and the type of data used. Moreover, the relationship between energy consumption and consumer activities is often simplified using constant conversion factors, which neglects other important issues.

1.1.2 Demand-side management (DSM)

DSM is the energy management technique that is used to modify the load pattern of the consumer with the main objectives being to maintain the supply-demand balance and improve both economic viability and energy efficiency (Kanakadhurga & Prabakaran, 2022). DSM can be broadly categorised into two parts. The first part involves the replacement of inefficient older equipment with more efficient versions. The second part, commonly referred to as demand response, encourages consumers to shift their demand in response to incentive payments or pricing schemes (Kanakadhurga & Prabakaran, 2022). This PhD research focuses on the second part, as it relates directly to household activity schedules, an area yet to be thoroughly explored.

Several DSM experiments have been conducted in the real world (Yilmaz, Weber & Patel, 2019; Bintoudi et al., 2021; wang et al., 2021). Generally, DSM is treated as an optimisation problem with objective functions such as minimising grid-sourced electricity consumption (Bissey, Jacques & Le Bunetel, 2017), reducing consumer electricity bills (Tushar, Zeineddine & Assi, 2018), decreasing peak loads (Nan, Zhou & Li, 2018), lowering the peak-to-average ratio (PAR) (Ahmad et al., 2017), optimising the total cost from investment to operation (Yang et al., 2021), reducing carbon emission (Pallonetto et al., 2019) and minimising consumer dissatisfaction (Shafie-Khah & Siano, 2018). DSM in the residential sector can involve various energy assets

such as indoor loads, EV charging loads, heating, ventilation, and air conditioning (HVAC) loads, energy storage systems and renewable energy generation. Consumer preferences, comfort, and behaviours are considered when the indoor load and HVAC load are included in the management. However, these consumer-related factors are usually represented by strat time ranges of activities in most literature. Such oversimplification fails to fully represent consumer preferences and behaviours in responses to electricity tariffs and DSM, resulting in gaps between estimated and real improvements in energy efficiency.

1.1.3 Research gaps

Consumer activities and behaviours are the key factors in driving electricity consumption and reshaping load profiles in the residential sector. However, these factors are often oversimplified or overlooked in energy demand modelling and DSM, as outlined below:

- (1) Most research in energy demand modelling and DSM is based on indoor activities and travel activities drawn from different contexts due to the challenges of accessing real-world data. This approach neglects the connections between indoor and travel activities (Dubey & Santoso, 2015; Leemput et al., 2014; Ho et al., 2014; Ihekwaba & Kim, 2017).
- (2) Linear relationships between activity types and energy consumption are usually established. However, the energy consumption of consumer activities is not solely determined by the activity type but is also influenced by other factors, such as the timing of activities and the interaction between simultaneous activities. For example, Grünwald & Diakonova (2019) showed that the marginal demand contribution of household activities can vary or even turn negative when paired with other activities. Additionally, machine learning (ML) algorithms, while popular in non-linear prediction problems in other domains, are rarely employed to generate residential load profiles based on influential factors such as activity patterns, socio-demographics and electricity prices.
- (3) DSM inherits the bias in the energy demand modelling and fails to fully capture the impact of consumer activities. For example, most DSM research reshapes the load profile by rescheduling the timing of certain household activities that are deemed to be flexible by the analyst. Subsequently, the same level of

demand driven by these activities is assumed to shift to the new time slots. With such an approach, the estimated impact of DSM policies may be biased and inaccurate.

- (4) Consumers' adaptation of household activities in response to DSM policies is usually assumed to be rational, driven by the desire to reduce monetary cost and restricted by simple ranges of activity start times. However, additional factors such as electricity prices and socio-demographics can play important roles in these behaviours.

These simplifications and assumptions may contribute to bias in modelling energy demand profiles and implementing DSM in the real world. These formed the primary motivations that shaped this PhD research, instigating this in-depth study into the role of consumer activities and behaviours in energy demand modelling and DSM.

1.2 Research aim and objectives

This PhD research aims to enhance energy demand modelling and DSM in residential sectors by integrating consumer activities and behaviours. The specific objectives that are designed to address the research gaps identified in the previous section include:

- (1) Objective A: Introduce the connection between consumer indoor activities and travel activities in load profile generation models.

The first objective is to generate residential load profiles that include indoor residential loads and coordinated EV charging loads in the residential area. Since EV charging loads and indoor residential loads are both derived from consumer activities, the key task in generating coordinated load profiles is to capture the connection between indoor activities and travel patterns. Consequently, the novelty of this objective lies in the usage of cohesive activity profiles within which indoor activities and travel patterns belong to the same individual and are therefore consistent with each other. Although separate models are required to generate EV charging loads and residential loads due to different estimation methods, this approach preserves the connection within activity profiles. This objective also establishes and validates the linear activity-to-power conversion factors prevalently used in the literature, to assess the accuracy of this type of load profile model, and to inspire the exploration of non-linear relationships between indoor activities and electricity consumption.

- (2) Objective B: Assess different methods and develop guidelines and recommendations for ML-based load profile models.

The second objective of this PhD research is to improve the state-of-the-practice in ML-based load profile modelling by assessing different methods and developing practically applicable guidelines. In order to achieve this objective it will be necessary to conduct comparative research on the details of energy demand models, including various influential factors, ML algorithms, and model parameters. Moreover, a novel feature engineering approach needs to be designed to capture the impact of the interaction between indoor activities on electricity consumption.

- (3) Objective C: Design a hybrid DSM model that considers consumer activities and interactions between them.

The third objective is to design a hybrid DSM model that considers cohesive travel and indoor activity profiles through the framework designed in Objective A thus producing a more realistic assessment of the energy-saving potential. Furthermore, factors that influence demand such as activity start time, socio-demographics and the interaction between activities will also be integrated through the preferred ML algorithm structure identified in Objective B.

- (4) Objective D: Generate new evidence and models that help us to better understand consumer behaviour in the context of DSM.

The fourth objective of this PhD research is to study consumer behaviours in terms of activity rescheduling and adaptation in the context of DSM trials. Since the identified gaps and previous objectives have demonstrated multiple influential factors in electricity consumption that are derived from indoor activities, it is reasonable to expect that these factors influence electricity consumption by influencing consumer activities and activity adaptation. To explore the impact of these factors, discrete choice models (DCM) are utilised instead of other activity-based models, e.g., time-allocation models, constraints-based models and computational process models (Rasouli & Timmermans, 2014a; Winston, 1987). DCMs are capable of modelling activity adaptation as a function of various influential factors, such as energy price, socio-demographics, energy-saving habits and attitudes, thus explicitly quantifying their significance and impacts. Specifically, the adaptation of six common household activities is studied, i.e.,

“Boil drinking water”, “Cook hot meals”, “Shower”, “Use a washing machine”, “Work” and “Leisure”. These activities were selected because they are prevalently reported in time-use surveys (Grünewald et al., 2017; Morris et al., 2016) and are widely rescheduled as main flexible electricity-consuming activities in DSM (Goyal & Vadhera, 2021; Bissey, Jacques & Le Bunetel, 2017; Bilton et al., 2014; Nazemi, Jafari & Zaidan, 2021).

Objectives A and B fall in the realm of energy demand modelling, while Objectives C and D pertain to DSM and behaviour modelling respectively. Figure 1.1 outlines the objectives and the link between them.

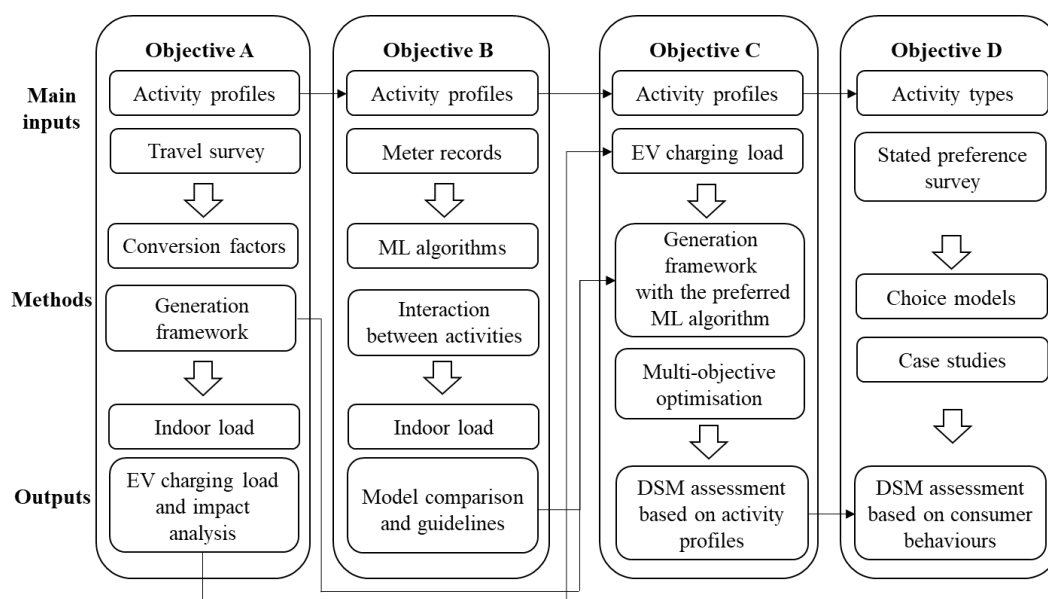


Figure 1.1 Links between objectives

1.3 Conceptual framework

Figure 1.2 illustrates the conceptual framework of this PhD research and the niche of each objective in the context of energy demand modelling and DSM.

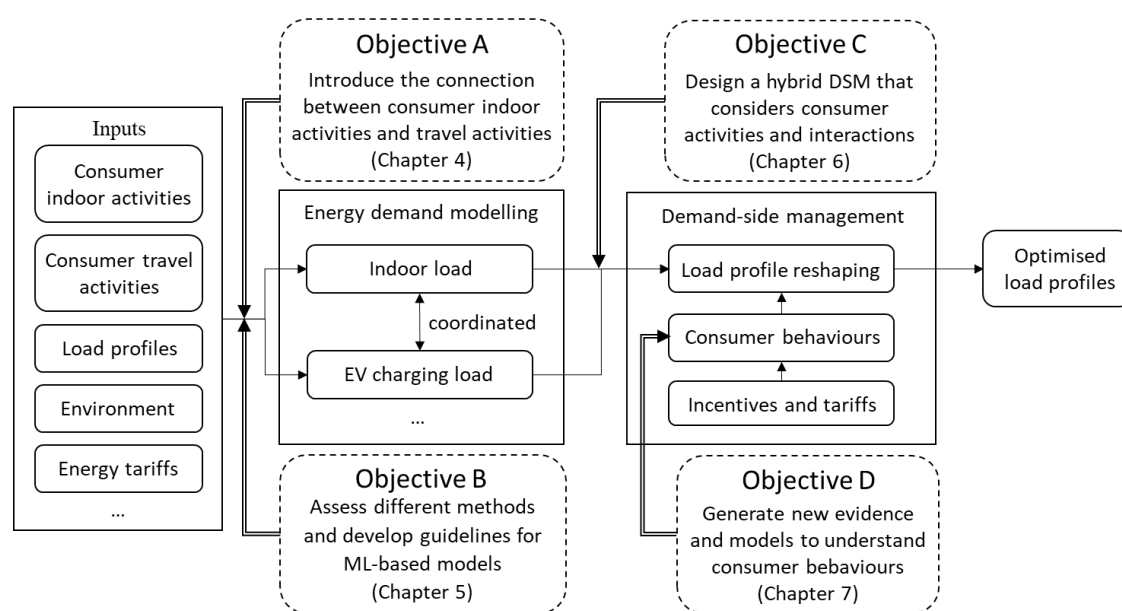


Figure 1.2 Conceptual framework

Energy demand modelling and DSM in the residential sector are tightly linked. Their input variables include historical energy consumption records and other influential factors such as consumer activities, weather and energy tariffs. Subsequently, the electricity consumption profiles of various energy assets in the network are generated based on these inputs. Among these energy assets, this PhD research focuses on indoor loads and EV charging loads, as they are common and constitute the major part of residential loads. The generated load profiles are usually volatile due to unscheduled indoor activities and EV charging. Such volatility can put considerable stress on the grid, reduce the efficiency gains from integrating renewables and increase consumer energy bills. Therefore, DSM employs price signals, incentive payments or direct control to reshape the load profiles according to the optimisation objectives. The final outputs are the optimised activity and load profiles with benefits such as more flattened curves, balanced supply and demand, and reduced consumer costs.

In the literature, consumer activities and behaviours were usually overlooked during the process of energy demand modelling and DSM. However, these factors are the primary drivers of electricity consumption and the principal determinants in adapting activity schedules. Therefore, this PhD research aims to enhance energy demand modelling and DSM by incorporating consumer activities and behaviours. Objectives A and B establish relationships between indoor activities, indoor loads, travel activities and EV charging loads in energy demand modelling instead of the more typical and

oversimplified estimation process. Objective C applies and tests this refined energy demand model in DSM, while Objective D digs deeper to understand consumer behaviours and choices in DSM. The aim is for these four objectives, which are part of a wider conceptual framework as shown in Figure 1.2, to lead to the development of more accurate and reliable energy demand models and DSM models in practice.

1.4 Outline of thesis

The rest of this thesis is structured as follows.

Chapter 2 provides a comprehensive review of energy demand modelling, DSM and the modelling of consumer behaviours in DSM. Data sources, assumptions and modelling methods are discussed to summarise the gaps and challenges.

Chapter 3 introduces the main datasets used in this PhD research. The major inputs for Objectives A, B, and C are secondary data comprised of simultaneous electricity consumption measures and activity records collected from UK households. Meanwhile, primary data for Objective D is collected through a stated preference survey regarding choices in changing activity patterns in response to ToU electricity tariffs in DSM.

Chapter 4 addresses **Objective A** and incorporates the connection between indoor activities and travel activities into load generation. Load profile generation models based on conversion factors are built to estimate both indoor loads and EV charging loads in the same context. The performance of this kind of model is assessed regarding the role of time-use survey and conversion factors. The impact of EV charging loads on the residential network is analysed with three charging strategies.

Chapter 5 tackles **Objective B** and designs three sets of scenarios to discuss details in ML-based load profile generation models. A novel feature “TimeCredit” is designed to represent the overlap and interaction between simultaneous activities. The results of six ML-based load profile generation models are compared in three sets of scenarios: (a) eight “meter-based”, “survey-based” and “meter-and-survey-based” input scenarios; (b) four scenarios with different widths of historical time windows; (c) two train-test split methods, “within data source” and “between data sources”.

Chapter 6 addresses **Objective C** and combines the models in Chapters 4 and 5 to build a hybrid optimisation model for DSM. This chapter compares the potential for improvement through DSM based on real activity profiles and simulated activity

profiles. The results underscore the importance of considering the connection between indoor and travel activities and offer insights for the design of ToU tariffs.

Chapter 7 covers **Objective D**, conducting a stated preference survey and building mixed logit models to study the choices in response to ToU tariffs. Case studies are designed to demonstrate the application of these choice models and explore the impacts of ToU tariffs at different price levels. The results reveal potential savings in consumer energy bills and changes in electricity load profiles. Distributional impacts are analysed in terms of annual income, presence of children and UK regions.

Chapter 8 concludes this PhD research by summarising the main contributions of this PhD research, discussing limitations, and proposing avenues for future work.

Chapter 2

LITERATURE REVIEW

2.1 Overview

This chapter reviews bottom-up modelling approaches in short-term energy demand modelling and demand-side management (DSM) within the residential sector. The typical profiles studied in this domain are the daily electricity consumption profiles of aggregated or disaggregated residential units. These profiles are generated, managed and optimised in the context of energy demand modelling and DSM. Specifically, this chapter reviews four aspects:

- (1) The generation of household indoor load (Sections 2.2.1 and 2.3.1)
- (2) The generation of electric vehicle (EV) charging load (Sections 2.2.2 and 2.3.1)
- (3) The mechanisms for reshaping load profiles in DSM (Section 2.3.2)
- (4) Consumer behaviours and interests in DSM (Section 2.4)

The relationship between these four aspects in energy demand modelling and DSM is shown in Figure 2.1.

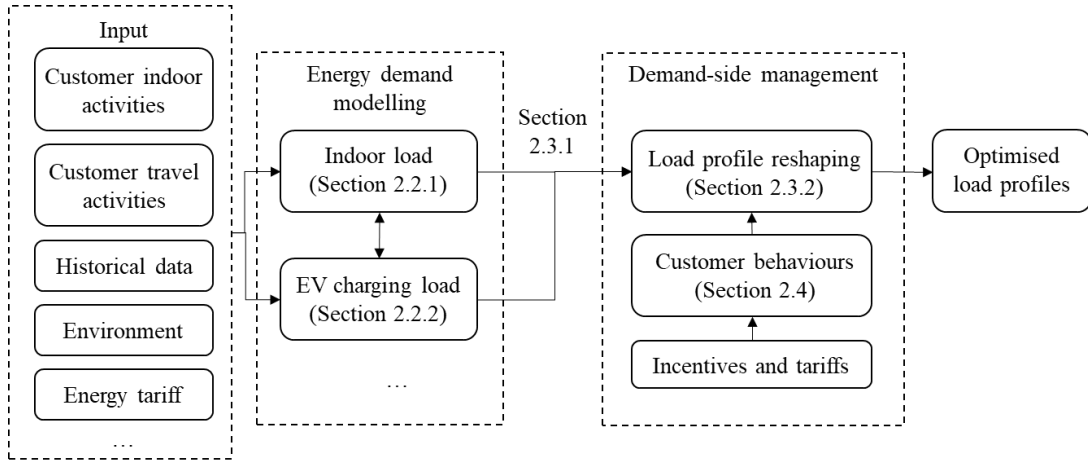


Figure 2.1 Relationship between four aspects in this chapter

Indoor loads and EV charging loads are intensively researched components in energy demand modelling but have usually been studied separately without considering their interconnections. Additionally, these two kinds of loads are important inputs for DSM

but are often oversimplified in DSM research, which may lead to a biased estimation of the potential for improvement. Consumer behaviour models and the load profile reshaping mechanisms determine consumers' response to DSM and the adaptation of load profiles. These models and mechanisms are therefore key to the implementation of DSM but are less studied.

2.2 Energy demand modelling

Short-term bottom-up energy demand modelling in the residential sectors is an important research domain to facilitate the management and operation of electricity networks and power plants. In addition, the recent rapid development of private EVs extends the research scope to include EV charging loads. This section presents a comprehensive review of both indoor load modelling and EV charging load modelling.

2.2.1 Indoor load modelling

Indoor load profile models can be categorised as generation models and prediction models according to the inputs and the underlying notion. Generation models leverage the similarity between load profiles of different units and the causality between electricity consumption and consumer activities. On the other hand, prediction models largely rely on the correlation between historical load and future load.

2.2.1.1 Load generation models

Load generation models are further classified by Grandjean, Adnot & Binet (2012) into three groups: (a) statistical random model, (b) probabilistic empirical model and (c) time of use based model. The first two groups of models analyse typical load profiles, occupancy profiles, or the probabilities of appliance usage of a larger number of units. Subsequently, the load profiles of the target unit are simulated and tuned based on its corresponding characteristics, such as socio-demographics and appliance ownership. For example, Yao & Steemers (2005) adopted the average daily electricity consumption of household appliances and household occupancy patterns from the literature. Then the start times of the appliance usage were repetitively selected at random within occupancy periods to obtain random appliance load profiles. These random appliance load profiles were subsequently aggregated and averaged to generate specific or typical daily household load profiles. Chuan & Ukil (2015) introduced a starting probability function to determine when an appliance will be activated based on the mean daily

starting frequency of appliances. The load patterns of appliances, such as working power and duration per cycle, were extracted from the internet and literature. Consequently, the load profiles were simulated for different types of households where the starting frequency of appliances varies.

The last group, although named by the author as the “time of use based model”, simulates energy demand based on the activities extracted from time-use surveys. The underlying notion argues that energy demand is derived from energy-consuming activities. Then, activity-to-power conversion factors were designed to generate energy demand profiles based on time-use surveys. For instance, Widén et al. (2009) extracted the standard powers and runtime of electrical appliances from product tests and assigned these load patterns to the recorded operating time of appliances in household activity surveys. This PhD research renames this group of models as the “survey-based” model to avoid the confusion between the original name “time of use based model” and time of use tariffs. This new designation emphasises the use of survey data as the primary source of inputs, distinguishing it from the “meter-based” load prediction models that rely on meter data. Validation against meter records demonstrated that these conversion models can reproduce realistic end-use composition, hourly demand variation and demand diversity among households (Widén et al., 2009; Widén & Wäckelgård, 2010). The “survey-based” models can generate load profiles specific to a day but require simultaneous activity records and energy demand measurements for validation (Grandjean, Adnot & Binet, 2012). Such data collection can be costly intrusive, and potentially unsustainable over long time horizons.

Load generation models establish a direct connection between household characteristics and electricity consumption, which facilitates energy demand modelling in new contexts. For example, the load generation model can predict future energy demand by updating the parameters in the presence of new technology or more energy-efficient appliances. Similarly, they can simulate changes in the load profile resulting from consumers’ responses to incentives or energy prices, such as adapting the timing and power rate of energy-consuming activities and appliances. Therefore, load generation models are widely used in strategic and policy-making energy research domains such as impact analysis and DSM. Dubey & Santoso (2015) generated daily load profiles by averaging measured hourly load demand for the impact analysis of EVs. Ihekweba & Kim (2017) used a typical daily load variation in California in the impact

analysis of EVs. However, these generation models usually overlook differences in activity patterns across households and simplify the impact of contextual factors such as weather, household socio-demographics, simultaneous activities and energy price.

2.2.1.2 Load prediction models

Prediction models, on the other hand, focus on forecasting energy demand in the future by drawing patterns from historical meter data. The inputs for these meter-based models offer a large quantity of data points (i.e., sample size and time scale) but fewer supplementary features (e.g., weather and occupant number). Such data are arguably becoming increasingly accessible from various smart metering technologies, providing an opportunity to collect sizeable datasets (Bissey, Jacques & Le Bunetel, 2017; Kim et al., 2019; Somu, M R & Ramamritham, 2020). Machine learning (ML) algorithms are usually utilised to capture non-linear relationships in prediction models based on such historical thin and large datasets. Dong et al., (2021) predicted building electricity consumption based on ensemble learning structure and energy consumption pattern classification. Energy consumption data from over 500 buildings for one year were firstly classified into corresponding categories by decision trees and then each pattern was predicted by ensemble learning methods with meteorological data. Somu, M R & Ramamritham (2020) utilised long-short-term memory (LSTM) networks for accurate and robust building energy consumption forecasting. The main inputs were historical building energy consumption data and climatic data over two years. High accuracy can be achieved in the prediction models due to the consistency of energy demand and the cyclic schedule of activity (Schirmer, Geiger & Mporas, 2021). Therefore, prediction models are common in load forecasting and building energy simulation due to their high accuracy, non-intrusive data collection method and simple data feature requirement. However, their application in DSM is limited due to the absence of a connection between consumer activity patterns and energy demand. Additionally, the accuracy of this approach relies heavily on the quality and size of historical data, which can make data collection time-consuming.

2.2.2 EV charging load modelling

Three key influential factors – travel patterns, EV parameters and charging behaviours – are central to estimating short-period EV charging load. EV parameters are generally referenced from car manufacturers, and charging behaviours are usually selected from

typical charging strategies. The last factor, EV travel patterns, which have been the primary focus of most research in this area, is typically extracted from travel surveys or activity-travel profiles. A detailed review by Daina, Sivakumar & Polak (2017) grouped these EV travel pattern models into three categories: (a) summary travel statistics models, (b) activity-based approaches, and (c) Markov chain models. This review pointed out that although EV travel patterns are likely to change due to future charging modes, prices, preferences and infrastructures, it is common to use conventional (i.e. non-electric) vehicle travel patterns to model EV use. Ho et al. (2014) utilised an activity-based approach with a Multi-Agent System (MATSim) to simulate the impacts of EV charging in Singapore. In MATSim, travel plans were simulated for each driver according to the random resident address and workplaces. Then the EV charging demand was estimated based on the characteristics of a common EV model (The Nissan Leaf), as well as the driving distance and driving time derived from travel plans. Duan et al., (2018) used a summary travel statistics model to estimate the EV charging loads for multiple regions. For each region, the EV charging capacity was the product of the total number of cars, forecasted EV penetration ratio, energy efficiency and the mean annual mileage. Then two charging modes, uncontrolled and coordinated, were considered to distribute the charging capacity over a day. Fischer et al. (2019) combined the information from national mobility datasets with a Markov-chain model to simulate EV usage. The number of cars per household, the first departure time and parking time were estimated based on household type, economic status and the driver's occupation. Then an inhomogeneous Markov-chain model, coupled with probability distributions, was employed to generate the sequence of destinations, driving mileage, and the duration of driving and parking. These parameters were subsequently used to calculate EV charging demand. In addition, individual charging behaviour was modelled using a logistic function that considered the driver's sensitivity to battery charging status.

An alternative approach to estimating short-period EV charging loads is the data mining method based on historical charging data. Xydias et al. (2013) used decision tables and machine learning methods to model EV charging loads, leveraging real-world charging demand and distribution curves from an EV project in the USA. Ihekweba & Kim (2017) utilised EV charging records collected from EV users and multiple EV charging stations in Los Angeles to analyse the EV charging impact. Zhao et al. (2021) developed a data-

driven framework for large-scale EV charging demand prediction, combining linear and nonlinear models. This framework incorporated real-world EV charging profiles from China's national EV big data platform with variables including vehicle states (e.g., total driving distance), subsystem data (e.g., the total voltage of the battery) and locations. These novel variables along with regional climatic data were fed into the data-driven framework, resulting in high-precision predictions. However, due to the limited access to real EV charging records, data mining methods are less prevalent in the current research landscape.

2.2.3 Summary

In summary, data accessibility is still a significant challenge in energy demand modelling. Simultaneous activity records and energy demand measurements are rare to support the study of the connection between them. In addition, it is difficult to obtain real data for both EV charging and indoor residential loads in the same context. As a consequence, EV charging loads and indoor residential loads are usually estimated based on separate datasets that have limited connections as shown in Table 2.1. Table 2.1 summarises papers that consider both indoor residential loads and EV charging loads in the impact analysis of EVs and demand-side management. It also displays the unconnected data sources for travel patterns and indoor loads, alongside the models and indicators analysed to articulate the current state of knowledge and identify gaps in this research domain. Unconnected indoor and outdoor activities may result in an inaccurate estimation of demand flexibility. Similarly, corresponding unconnected load profiles may generate peak loads with inaccurate timing and magnitude. Muratori (2018) started to address this limitation by using load profiles generated from cohesive activity profiles. However, these activity profiles were generated based on average statistics, which is hard to validate and omits activity details such as travel purposes and travel modes. In addition, while the impact analysis based on typical load profiles in large spatial scales such as cities and districts is prevalent, studies at the household level are scarce, resulting in an inadequate understanding of activity variability and load flexibility.

Table 2.1 Summary of impact analysis and demand response studies

Reference	Research domain	EV charging load		Residential load		Analysed indicators
		Travel pattern data	Model	Data source	Model	
Leemput et al. (2014)	Impact analysis	Transportation behaviour in Flemish, Belgium.	Summary travel statistics	Household electricity consumption profiles in Flemish, Belgium	Stochastically representative sample	Load profile, voltage magnitude profile, voltage unbalance profile
Salenbien et al. (2014)	Impact analysis	Transportation behaviour in Flemish, Belgium	Summary travel statistics	Household electricity consumption profiles in Flemish, Belgium	Synthetic load profile	One percent peak power (OPP), self-consumption, utility factor of EV
Dubey & Santoso (2015)	Impact analysis	–	Deterministic load profile	Hourly load demand measured at the substation; monthly demand	Averaging over the year; scaling	Voltage variability, EV accommodation capacity
Ihekwaba & Kim (2017)	Impact analysis	–	EV charging records in Los Angeles	Typical daily profiles in different seasons in California	–	Load profile
Ho et al. (2014)	Impact analysis	Road map of Singapore, designed activity plan	Activity-based approaches: simulation with MATSim	Load profile for Singapore	Average day	Load profile

Lin et al. (2018)	Impact analysis	US National Household Travel Survey; EVs charging patterns from North American and Irish	Activity-based approaches	Open Energy Information	A typical load of summer days	Electricity consumption, energy cost, energy price
Fischer et al. (2019)	Impact analysis	Mobility behaviour survey in German	Markov-chain	–	The load profile generator synPRO, average daily load profile	Absolute annual electricity demand, load profile, Electricity peaks
Sun, Neumann & Harrison (2020)	Demand-Side Management	The U.K. National Travel Survey	Summary travel statistics	–	U.K. Individual high-resolution synthetic residential load profile	–
Kurniawan et al. (2020)	Demand-Side Management	User's guide for the transportation sector and the Indonesia 2050 pathway calculator	Summary travel statistics	The load profile from different types of consumers in Jakarta, Indonesia	Aggregating a typical daily load profile for the urban medium voltage grid	–
Nan, Zhou & Li (2018)	Demand-Side Management	–	Summary travel statistics	Smart grid application demonstration project in China	–	–

2.3 Demand-side management (DSM)

DSM is the energy management technique that is used to modify the load pattern of the consumer (Kanakadhurga & Prabakaran, 2022). A typical residential DSM usually leverages consumer activities and load profiles as fundamental inputs. Motivated by energy price signals or incentive payments, consumers or the controller will reshape the activity and load profiles to meet objectives such as minimal electricity consumption, minimal cost and bills, and uncompromised consumer comfort. This section focuses on the load profile inputs and load profile reshaping mechanisms, while the next section focuses on consumer behaviours in DSM.

2.3.1 Load, activity and EV usage profiles in DSM

Most load profile generation methods in DSM research inherit the drawbacks of energy demand models, which typically overlook the connection between indoor load profiles and EV charging load profiles as outlined in Section 2.2. Specifically, the indoor activity and load profiles are usually simulated based on probability distributions (Durillon et al., 2020), predefined or averaged typical profiles (Anvari-Moghaddam et al., 2017; Kurniawan et al., 2020), or monitoring data (Nan, Zhou & Li, 2018; Fotouhi Ghazvini et al., 2017). Meanwhile, EV charging load profiles are generally estimated based on the efficiency of EVs and the normally distributed travel patterns, such as arrival and departure time, as well as mileage (Liu et al., 2018; Nan, Zhou & Li, 2018; Sun, Neumann & Harrison, 2020) (Table 2.2). For instance, Korkas et al. (2022) proposed a DSM method for grid-connected buildings considering both energy cost and thermal comfort. The flexible thermal load and unflexible building loads were generated utilising both building simulation software EnergyPlus and typical residential load profiles. On the other hand, the EV usage was estimated based on simple ranges of parameters, such as arbitrary EV arrival state of charges (SOC), arrival time and departure time. The author analysed the robustness of introducing different parameters including EV properties, resulting in acceptable degradation of performance. However, the adoption of a typical uncontrollable building load profile and assumed EV usage patterns may result in exaggerated demand flexibility and the overlook of household diversity. Particularly, the arrival time of EVs can range from 00:00 to 21:00 while the allowed departure time needs to be at least two hours after the arrival. This assumption offers a long flexible charging period throughout most of the day which may not be

achieved in the real world. Angizeh et al. (2022) designed a novel hierarchical DSM framework for a community network comprised of four buildings, a solar-plus-storage system, an emergency generator and an EV charging station. Due to the limited real data for the housing complex in that community, load profiles were simulated based on the profiles of large hotels. Similarly, the EV charging demand was estimated based on arbitrary or random parameters, including charging time, number of working chargers and initial SOC.

Table 2.2 Summary of demand-side management studies

Reference	Activity profiles or indoor load profiles	EV usage
Anvari-Moghaddam et al. (2017a)	Ten sets of simulated household load profiles	-
Fotouhi Ghazvini et al. (2017)	Obtained from public dataset	Predefined arrival and departure time
Liu et al. (2018)	Simulated based on typical daily load profiles through surveying	Normally distributed EV charging start time
Nan, Zhou & Li (2018)	Monitored residential load profiles	Normally distributed daily departure time, arrival time and travel distance
Sun, Neumann & Harrison (2020)	U.K. Individual high-resolution synthetic residential load profiles	Normally distributed daily departure time, arrival time and travel distance
Kurniawan et al., (2020)	Aggregating a typical daily load profile for the urban medium voltage grid	Normally distributed daily departure time, arrival time and travel distance
Durillon et al. (2020)	Simulated based on the probability of daily household activities	Normally distributed daily departure time, arrival time and travel distance
Nazemi, Jafari & Zaidan (2021)	Predefined schedule for flexible appliances	Predefined charging schedules
Bintoudi et al., (2021)	Formulated by the open-source algorithm LoadProfileGenerator based on the summation of real measurements from various appliances	-
Cerna & Contreras, (2021)	Simulated profiles based on the assumed usage and preference of indoor appliances	Assumed charging pattern

Huang et al. (2022)	Simulated profile based on occupancy schedules and lighting usage in Sweden	Estimated based on the Swedish Travel Survey
Tostado-Véliz et al. (2022)	Six real profiles	Predefined charging schedules

This approach of simulating indoor loads and EV charging loads independently overlooks the intertwined relationship between an individual's indoor activities and travel behaviours. The periods of EV charging and indoor activity usually overlap and correlate. One example is that the flexibility of indoor activities and EV charging loads is constrained not only by consumer preferences but also by the arrival and departure times of the vehicles. Therefore, the disconnect between indoor activity and EV usage may lead to an overestimation of their flexibility and an exaggerated potential for improvement in DSM. Particularly, when independent indoor and outdoor activity profiles are utilised, few studies consider indoor occupancy schedules and consumers' multiple travel activities associated with the same vehicles. In this context, Figure 2.2 illustrates the comparison between feasible and assumed flexibilities of the indoor activity start times and EV charging periods in cohesive activity profiles and independent activity profiles.

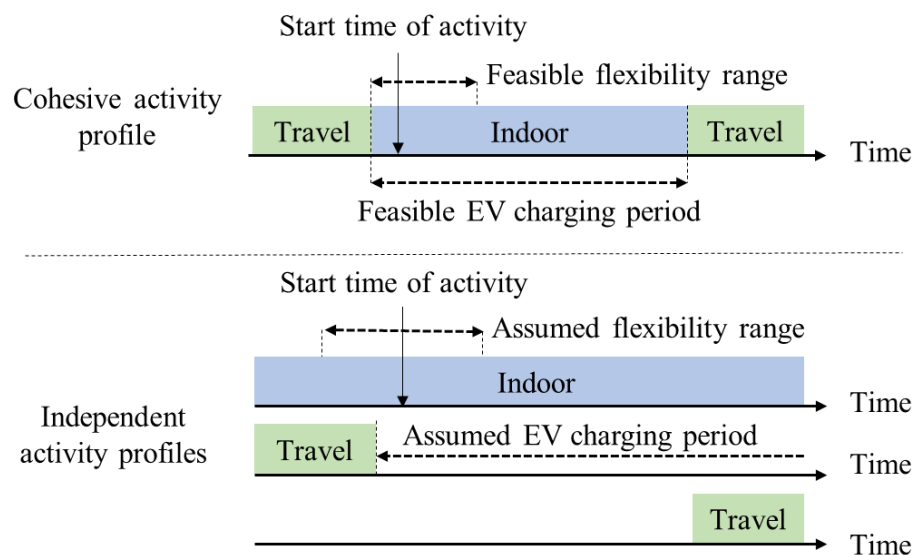


Figure 2.2 Exaggerated potential for improvement in DSM

Furthermore, although such an independent and simple load profile simulation method may work well for a large case study, it may cause biases in other cases. Particularly, the travel patterns of EVs may not be normally distributed in small datasets. For

example, in the smart home context, the assumption of normally distributed EV usage was common (Fotouhi Ghazvini et al., 2017) but the sensitivity analysis of such assumptions is scarce in the literature. Likewise, grid-level DSM also uses normally distributed EV usage patterns even for networks with less than 200 households (Nan, Zhou & Li, 2018; Sun, Neumann & Harrison, 2020; Durillon et al., 2020). However, non-normally distributed car travel patterns were observed in the datasets presented in Chapter 6 of this thesis and other literature (Ihekweba & Kim, 2017; Sørensen et al., 2021; Kim, 2019).

These two potential sources of bias in analysing DSM strategies have neither been discussed nor validated in the literature.

2.3.2 Load profile reshaping mechanisms

Most DSM research assumes constant activity-to-load conversion factors, which fails to consider other factors that can influence demand. Consequently, current DSM models reshape the load profile by rescheduling flexible household activities and shifting the same activity-driven load pattern to the new time slots. In other words, the indoor loads at any given time slot are the sum of products of constant energy intensity and a binary variable of activity occurrence (Anvari-Moghaddam et al., 2017; Xiang et al., 2020; Wang, Zheng & Zhou, 2021) (Figure 2.3).

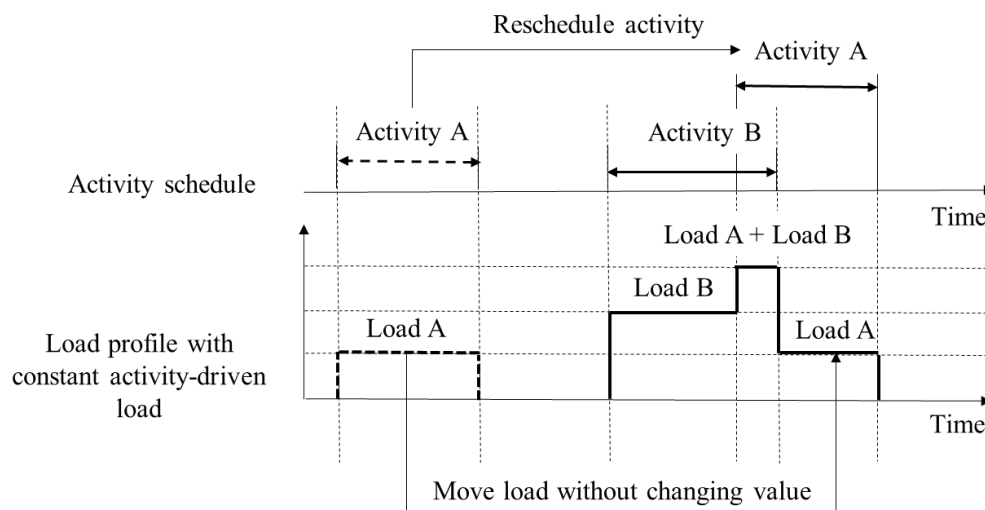


Figure 2.3 Load profile shifting

However, the electricity consumption of activities is not only influenced by the activity type but also by other influential factors, including the time of day, the tariff and the interaction between simultaneous activities. For example, the electricity intensity of

activities is expected to be inversely related to the electricity tariff. What is more, Grünewald & Diakonova (2019) analysed the load of multiple simultaneous activities. The results show that the marginal load contribution of the activity can vary or even be negative when paired with other activities. One example is the negative marginal load attribution of the activity “wash dress” to the activity “washing machine”. One potential reason can be that when both activities occur simultaneously, part of the clothes are hand-washed or only the daily clothes are washed instead of heavier items like bedsheets. Therefore, the washing machine can operate in a lower electricity-consuming mode. The study of these influential factors can provide a more comprehensive perspective of human behaviours and their impact on energy consumption (Carlucci et al., 2020).

To relax this simplified assumption of constant activity loads, another type of residential load, the ‘adjustable load’ or ‘power flexible loads’, was designed in the literature to be distinct from the shiftable load and interruptible load mentioned above (Zou et al., 2023; Angizeh et al., 2022; Durillon et al., 2020; Nan, Zhou & Li, 2018). The power rate of these adjustable loads can be adjusted in DSM. However, these adjustable loads in the literature are usually related to HVAC loads, EV charging loads and storage loads rather than common indoor activities (Nan, Zhou & Li, 2018; Durillon et al., 2020). What is more, while this new category of loads provides a flexible range for activity power, the factors that influence activity loads remain under-researched.

2.4 Consumer behaviour modelling in DSM

2.4.1 Consumers’ decisions in DSM

DSM can involve components such as the electricity grid, energy suppliers, buildings, management systems, consumers and electricity-consuming devices. It is acceptable to simplify consumer interests and preferences when DSM operates at a macro level or involves only automated components, which bear less association with human comfort and consumer behaviours (Good, 2019). On the contrary, consumers’ decisions need to be further studied in micro-level residential DSM since it is deeply embedded in energy investment and activity adaptation. While most literature focuses on the former investment process, the latter is rarely studied. Hille, Weber & Brosch (2019) studied consumer preferences in subscribing to electricity-saving programs exploring features such as goal setting, reward and penalty schemes. Yilmaz et al. (2020) conducted a

survey to measure consumer preference for electricity tariffs and direct load control (DLC). The results show that socio-demographic and dwelling characteristics have a great impact on the interest in tariffs, while the acceptance of DLC varies across different appliances. These findings stress the heterogeneity of consumer preferences in DSM and suggest that socio-technical dynamics are a key factor in achieving high participation in DSM. Herre et al. (2022) investigated the impact of lead time on the demand flexibility of consumers in DSM and found that the price elasticity of consumers can vary depending on the lead time. Janmaimool & Chontanawat (2021) has examined the impacts of cognitive and affective factors on university students' participation in sustainable energy behaviours (SEBs). The findings reveal that cognitive factors, aiding rational thought processes, play a critical role in participation in SEBs. Significant factors include concerns about the impact of energy behaviours on climate change, perceived self-efficacy, and perceived self-interest.

Consumers' rescheduling of activities in DSM is usually simplified as the change of activity start times within a time range but additional influential factors during this rescheduling process need further exploration. Good (2019) grouped behaviours into routine and deliberative categories. Routine behaviours are repetitive and highly influenced by habits and contexts while deliberative behaviours are invoked in response to more significant and less frequent choices. The author proposes that a behavioural economics-based approach, which uses psychology and microeconomic theory to incorporate bias in decision-making, is suitable for modelling deliberative behaviours. Furthermore, energy-related deliberative behavioural issues are classified into three groups: (a) investment in energy efficiency; (b) response to time-of-use (TOU) tariffs; and (c) energy trading amongst distributed autonomous agents. The author concludes that consumer preferences and biases can influence DSM but have not been fully studied. Mohseni et al. (2022) systematically reviewed the academic articles on modelling renewable and sustainable energy systems. One important conclusion of the review work is that the current DSM energy planning still lacks consideration of social and behavioural factors. The author also suggests that targeted and personalised behavioural DSM programmes under uncertainty should be developed by leveraging feedback from participants. Vellei, Martinez & Le Dréau (2021) point out that consumers' interactions with thermal systems can be influenced by both physiological conditions and psychological situations, which in turn depend on socioeconomic

characteristics and dwelling characteristics. The author then proposes that these factors should be incorporated into future agent-based models as new attributes.

In summary, existing literature has explored the impact of multiple influential factors, such as socio-demographics, dwelling characteristics and cognitive factors, on consumers' preference towards SEBs and ToU tariffs. Similarly, factors such as goal setting, reward, penalty schemes and lead time have been examined in the context of consumer participation in DSM events with incentives. However, the impacts of these factors on consumers' specific activity adaptation in ToU tariffs and DSM have not been studied. Consequently, Chapter 7 aims to bridge this gap. The studied influential factors are selected from the literature, including socio-demographic (e.g., age and gender), dwelling characteristics (e.g., type of the living property and the ownership of equipment) and cognitive factors (e.g., environmental concerns and perceived self-benefit). Not every factor within these categories as identified in the literature is selected or directly recorded due to data collection limitations. For example, education level is not collected and household composition is measured through separate questions regarding the number of children, adults and older adults.

The next two Subsections 2.4.2 and 2.4.3 focus on reviewing consumers' decisions on rescheduling activities in current DSM research. This thesis analyses consumer decision models along two dimensions as shown in Table 2.3. The first dimension is the consumer interest model, which includes three groups: static preference limits, physical models and data-driven models. The second dimension is the scale of the consumer unit, which can be an aggregated unit or a disaggregated unit. Finally, Subsection 2.4.4 reviews stated preference surveys and choice models. These methods have been widely used to study choice behaviours and influential factors in other research areas but are rarely used in DSM research to understand and model how activity patterns are modified.

Table 2.3 Consumer decision models in DSM:
Modelling methodology vs. scale of consumer unit

	Static preference limits	Physical model	Data-driven
Aggregated unit	(1) Cerna & Contreras (2021) (2) Nan, Zhou & Li (2018)	Yang et al. (2021)	Amasyali & El-Gohary (2021)
Disaggregated	(1) Svetozarevic et al.	Vellei, Martinez	

unit	(2022) (2) Zhang et al. (2021b) (3) Lu & Hong (2019) (4) Pinto, Deltetto & Capozzoli (2021) (5) Tang, Wang & Li (2019)	& Le Dréau (2021)	
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2.4.2 Consumer interest model

In DSM, consumer interests are usually represented in the form of static preference limits, physical models or data-driven models. Static preference limits for activities, such as flexible ranges of activity start time and minimal power rate, are particularly prevalent. Correspondingly, the optimisation model in DSM with static preference limits usually aims to maximise utility with minimum deviation from the limits. Cerna & Contreras (2021) designed an intelligent scheduling strategy for household activities, considering consumers' hourly preferences for appliance usage. The constraints in the optimisation model ensure that these appliances operate only during preferred periods. The author points out that defining the range of activity start times is complicated, as high flexibility may compromise consumer satisfaction while low flexibility may lead to simultaneous activities and peak loads. Therefore, the static preference limit is critical for DSM efficiency. The static preference limits can also be set for demand level or other influential factors. For example, Nan, Zhou & Li (2018) present a DSM model incorporating the static limits for both the power consumption and the activity start times. In that study, consumers can adjust the electricity consumption level of activities like lighting and air conditioning during periods of high electricity prices.

Physical models of consumer interest in the literature are usually related to physical environmental comfort, especially thermal comfort. Nazemi, Jafari & Zaidan (2021) demonstrated a multi-objective optimization approach for DSM in smart buildings. The desired hot water temperature, building indoor temperature and the maximum acceptable difference between the desired temperature and actual temperature were designed to maintain occupant comfort. At the same time, the hygrothermal equations and the dynamic energy balance equation were built to connect the temperature with energy consumption costs in the objectives. Yang et al. (2021) built a bi-level robust optimisation model for integrated energy systems to save energy while maintaining thermal comfort. The Predicted Mean Vote (PMV) index was calculated to show the

thermal comfort of occupants based on indoor environmental variables and human body characteristics. This PMV index was constrained within a specified range in the optimisation model to ensure comfort. Vellei, Martinez & Le Dréau (2021) calibrated a DSM application for thermostat adjustment. Environmental variables and body characteristics were fed into a two-node thermo-physiological model to simulate the temperature of the body core and mean skin temperature. Then a dynamic thermal perception model utilised these two types of temperature to predict the dynamic thermal comfort.

Data-driven models of consumer interests are rare due to the challenge of data accessibility. Amasyali & El-Gohary (2021) proposed a DSM model with the objectives of reducing energy consumption, as well as improving thermal and visual comfort. These three objectives were calculated by machine learning models with inputs including indoor environmental variables and the actions on various building components such as heating, lighting, windows and doors. An online survey tool, named Preference Monitoring Application (PMA), was utilised to collect the energy-related actions as inputs and occupant comfort as targets.

In summary, within these three categories of consumer interest models, static preference limits and physical models can design clear constraints or objectives for decision variables, such as the activity start time and the energy demand level. However, static preference models are too simple to accommodate other factors that influence changes in activity patterns in DSM, such as electricity prices and activity start times, and physical models usually focus on comfort in a single aspect. On the contrary, although data-driven models can predict consumer interests based on a large range of factors, the lack of a clear theoretical relationship between these factors and consumer interests obstructs the application of DSM in policy-making. Therefore, an interpretable quantitative consumer interest model considering multiple influential factors needs to be designed.

2.4.3 Scale of consumer unit

The consumer unit in DSM can be modelled using aggregate or disaggregate approaches. The aggregate approach integrates the interests of multiple consumers and pursues the optimal result from a holistic perspective. Although individual utility is not maximised, the deviation remains within an acceptable range. In an optimisation model

with aggregate consumer units, objectives usually include minimising the sum of the monetary energy expenses of all consumers and the constraints include consumer preferences (Yang et al., 2021; Cerna & Contreras, 2021; Nan, Zhou & Li, 2018). However, the optimisation result is the holistic optimal solution assuming consumers follow the designed strategy rather than individual consumers' response to the designed incentives or price signals.

On the other hand, the disaggregate approach allows consumers to pursue individual interests and interact with other network components. This approach introduces knowledge from game theory, agent-based simulation or reinforcement learning to model the interactions. de Souza Dutra & Alguacil (2020) propose a two-phase DSM framework to simulate the coordination between residential users. In the first phase, each consumer arranges the usage of appliances to optimise household energy consumption and personal comfort. In the second phase, the aggregator implements a coordination strategy to reduce the total cost while ensuring no economic losses or discomfort occurs among consumers. Tang, Wang & Li (2019) utilised game theory to simulate the bidirectional interaction between a grid and buildings. Stackelberg games based on Nash equilibria were developed to achieve a win-win situation. In the game of that study, the grid maximised the net profit and reduced load fluctuation by adjusting the price. At the same time, each building minimised its electricity bill by reshaping the hourly power demand.

Another disaggregate approach for considering consumer interests in DSM involves the integration of multi-agent simulation and reinforcement learning, which has developed rapidly in recent years. Multi-agent systems can simulate the interaction between a group of agents, and the interaction between the agent and the environment. In addition, instead of designing globally optimal strategies for agents, this approach respects the autonomy of agents and simulates the strategy of each agent according to individual characteristics (Kofinas, Dounis & Vouros, 2018). Reinforcement learning aims to explore the optimal behaviour strategy with the maximal reward for agents (Svetozarevic et al., 2022; Kofinas, Dounis & Vouros, 2018). Combining their advantages, multi-agent reinforcement learning has been widely used in DSM where multiple components are involved, such as a microgrid with multiple buildings, a residential sector with a group of consumers or a smart building with plenty of systems and devices. Kofinas, Dounis & Vouros (2018) built a cooperative multi-agent system

with a reinforcement learning method for a stand-alone microgrid. This microgrid consists of multiple power production, power consumption and power storage units. The experimental results show this disaggregate method can ensure the effectiveness of both individual agents and the whole system to guarantee the supply-demand balance and the reliability of the microgrid. Zhang et al. (2021b) propose a conceptual architecture for a price-based DSM that involves a diversified facility. In this model, a central controller periodically receives price signals. Each device is an agent equipped with functions of states, actions, policies and rewards. A laboratory-level testbed was built to evaluate the effectiveness of this architecture. Vellei, Martinez & Le Dréau (2021) designed an agent-based model to simulate the occupants' interactions with thermostats in residential buildings. Each occupant agent can trigger individual rule-based adaptive actions for thermal comfort. Then the DSM model predicts occupant responses and satisfaction based on these actions such as the modulation of air temperature setpoint.

In conclusion, the aggregate approach typically compromises homogeneous consumers' interests within a certain range, failing to capture consumers' real responses. On the other hand, although the disaggregate approach simulates individual behaviours, these behaviours are usually driven by energy efficiency, money savings and physical comfort. Therefore, more influential factors in consumer decision-making models should be considered at the disaggregated level in DSM.

2.4.4 Stated preference surveys and discrete choice models

Activity-based models, especially Discrete choice models (DCMs) are introduced in Objective D to better understand individual consumers' choices in activity scheduling in DSM. Activity-based models are usually used to predict the sequence of activities and associated travel conducted by individuals or households, subject to a set of spatial, temporal, institutional and possibly budget constraints (Rasouli & Timmermans, 2014a). Rasouli & Timmermans (2014a) categorised activity-based models into three groups: constraints-based models, utility-maximising models and computational process models. The primary purpose of constraints-based models is to check whether any given activity agenda is feasible in a specific space-time context, focusing on the time geography and space-time prism (Rasouli & Timmermans, 2014b). Utility-maximising models focus on preferences and are based on the premise that individuals

maximise utility in choosing alternatives. For example, DCMs assume individuals will choose an alternative that maximises the utility derived from the attributes of the alternatives (Lancaster, 1966) and the estimated coefficients of attributes show influences. Similarly, time-allocation models maximise the utility by allocating time and goods to preferred activities (Winston, 1987; Jara-Díaz et al., 2008). However, the estimation of time-allocation models usually requires detailed information on daily time use and the impact of influential factors is not displayed directly. Computational process models utilise various decision-making models, such as neural networks (Pendyala et al., 1997), decision trees (Arentze & Timmermans, 2004) and ordered probit model (Auld & Mohammadian, 2012), to depict decision heuristics in complex and dynamic systems. Objective D aims to understand individual consumers' activity adaptation behaviours in DSM and quantify the impact of factors such as energy price and socio-demographics. Therefore, considering the challenge of collecting detailed daily time use, consumers' choice regarding adapting several main activities is collected through surveys and DCMs are utilised to model the choices.

There are generally two prevalent methods to collect data about consumer choices through surveys: revealed preference (RP) surveys and stated preference (SP) surveys. RP surveys collect actual choices that are observed by researchers or reported by consumers. Although the RP survey is closer to real-world situations, its application in studying the choices of activity adaptation in DSM is limited due to the following challenges summarised by Ortúzar, Willumsen & Consultancy (2011):

- (1) Actual choices may present insufficient variability in terms of alternatives and attribute levels, resulting in poor statistical efficiency.
- (2) A limited number of attributes or factors may dominate the choice in the real world and make the influence of other attributes less likely to be captured.
- (3) It is hard to collect real choices in hypothetical situations or new contexts.

What is more, the difficulty of providing various incentives and energy tariffs in the real world turns the data collection method to SP surveys. Contingent valuation, conjoint analysis and stated choices are three SP methods. Since stated choice methods are the most dominant in modelling consumer choices (Ortúzar, Willumsen & Consultancy, 2011), SP refers specifically to stated choices hereinafter. SP surveys typically ask participants to choose a preferred alternative from a set of hypothetical

alternatives characterised by designed levels of attributes. Therefore, SP surveys have the advantage of capturing information with sufficient variabilities that the real world lacks. To construct effective SP surveys, researchers need to determine the proper number and characteristics of alternatives, attributes and attribute levels. For example, the range of alternatives needs to comply with the research objectives while maintaining realism. Similarly, the set of attributes should be sufficient to describe the alternatives but not excessive which may lead to participant fatigue. The levels of attributes also require careful design to cover a proper range and avoid too many combinations.

Subsequently, the following two types of stated choice experiment designs can be employed to determine the attribute level combinations in hypothetical situations (Louviere et al., 2000).

- (1) Full factorial design: All possible hypothetical situations are included in the design to ensure orthogonal main effects and interaction effects. However, this design will typically generate too many hypothetical situations.
- (2) Fractional factorial designs: There are numerous methods to select a subset of full factorial design and maintain some desirable features. For example, the orthogonal design is popular for the zero correlations between the attributes. On the other hand, the efficient design can minimise the variances and covariances of the parameter estimates with an equal or lower sample size. The most predominately used efficient design is called D-efficient design (Rose & Bliemer, 2009).

Choice models are typically utilised following SP data collection, facilitating the understanding of influential factors and the prediction of choice-making. Discrete choice models (DCMs), a popular model from the early 1980s, postulate that individuals' probability of choosing a given option is a function of their socioeconomic characteristics and the relative attractiveness of the option (Ben-Akiva & Lerman, 1985). In other words, in DCMs, individuals choose an alternative that maximises the utility derived from the attributes of the alternatives as moderated by the characteristics of the individuals (Lancaster, 1966). Accordingly, the observed utility is usually a linear combination of the product of coefficients and attributes. The most common theoretical framework behind DCMs is random utility theory (Williams, 1977) and the main assumptions include: (a) Perfect information is available to rational individuals from a

homogeneous population to choose the alternatives with max utility; (b) There is a certain set A of available alternatives and a set X of vectors of measured attributes x of individuals and alternatives; (c) Each alternative $A_j \in A$ has associated a net utility U_{jq} for individual q .

Since complete information is not available for the model builder, the utility U_{jq} can be represented by the sum of a measurable part V_{jq} and a random part ε_{jq} .

$$U_{jq} = V_{jq} + \varepsilon_{jq} \quad (2.1)$$

The measurable part V_{jq} is the function of the measured attributes x as the expression below, while the random part ε_{jq} can be random variables with a mean of 0 and a probability distribution.

$$V_{jq} = \sum_k \theta_{kj} \cdot x_{jkq} \quad (2.2)$$

where θ are constant parameters for all individuals in the homogeneous population.

The individual q chooses the maximum utility alternative A_j if and only if:

$$U_{jq} \geq U_{iq}, \forall A_i \in A(q) \quad (2.3)$$

which is:

$$V_{jq} - V_{iq} \geq \varepsilon_{iq} - \varepsilon_{jq} \quad (2.4)$$

And then the probability of choosing A_j is:

$$P_{jq} = Prob\{\varepsilon_{iq} \leq \varepsilon_{jq} + (V_{jq} - V_{iq}), \forall A_i \in A(q)\} \quad (2.5)$$

The joint distribution of the random part ε is unknown and can be denoted by $f(\varepsilon) = f(\varepsilon_1, \dots, \varepsilon_N)$. Therefore the probability can be rewritten as :

$$P_{jq} = \int_{R_N} f(\varepsilon) d\varepsilon \quad (2.6)$$

$$R_N = \begin{cases} \varepsilon_{iq} \leq \varepsilon_{jq} + (V_{jq} - V_{iq}), \forall A_i \in A(q) \\ V_{jq} + \varepsilon_{jq} \geq 0 \end{cases} \quad (2.7)$$

The equations above can be used to generate different discrete choice models depending on the distribution of the random part $f(\varepsilon)$.

This section briefly introduces two prevalent kinds of DCMs, the multinomial logit model (MNL) and mixed logit model, as they are suitable for this PhD research. MNL assumes that the random part ε follows an Independently and Identically Distributed (IID) Gumbel distribution (Tom Domencich & Daniel L. McFadden, 1975). Then the probability of choosing an alternative A_i is:

$$P_{iq} = \frac{\exp(\beta \cdot V_{iq})}{\sum_{A_j \in A(q)} \exp(\beta \cdot V_{jq})} \quad (2.8)$$

where β is the parameters.

MNL, while straightforward to apply, has drawbacks that limit its application in real and complex contexts. For example, the MNL has the property of “Independence from irrelevant alternatives” (IIA), which states that the relative preference of choosing an alternative A_i compared with A_j is irrelevant from the existence or utility of other alternatives. However, the famous paradox of the red-and-blue buses shows the failure of this property when alternatives are correlated. Another issue lies in the assumption of a homogeneous population where the coefficients do not vary across individuals, which neglects individual differences.

The mixed logit model can be derived under several behavioural specifications with particular interpretations. In general, the mixed logit model is defined based on the functional form for its choice probabilities as below (Train, 2009):

$$P_{jq} = \int L_{jq}(\beta) f(\beta) d\beta \quad (2.9)$$

where $L_{jq}(\beta)$ is the MNL logit probability at parameters β , and $f(\beta)$ is a density function. Then this probability is a weighted average of logit probability evaluated at different values of β , with weights given by the density $f(\beta)$. In general, the density $f(\beta)$ can be set as various distributions to approximate different models and used in particular contexts. For example, when $f(\beta)$ degenerates a fixed parameter b , the mixed logit model will become MNL as $f(\beta) = 1$ for $\beta = b$ and 0 otherwise. Therefore, the flexible $f(\beta)$ allows mixed logit models to address random coefficients, the correlation between alternatives and the multiple takes completed by the same individual over time (Train, 2009).

SP surveys and DCMs have been extensively applied in evaluating human preferences and predicting choices in marketing, urban planning, economics, environmental sciences and transport (Feneri, Rasouli & J.P. Timmermans, 2021). Czajkowski, Hanley & Nyborg (2017) utilised SP surveys and DCM to explore the impact of selfish, moral and social incentives and pressures on pro-environment behaviours. Viscecchia et al. (2019) employed SP surveys and latent class analysis to study consumer preference for a cheese product characterised by attributes such as nutrition claims and health claims. Badiola, Raveau & Galilea (2019) developed an SP survey to collect people's preferences towards daily activities and the impact of preferences on departure time choices. The results suggest that the activities to be conducted before and after trips should be considered in modelling and forecasting departure time and travel demand. Manca et al. (2021) collected consumer attitudes toward air travel during and post the pandemic using RP and SP surveys. A hybrid choice model was built to integrate latent constructs related to attitudinal characteristics. However, as stated in Section 2.4.1, the application of DCMs in DSM is limited.

2.5 Summary

This chapter presents a comprehensive literature review on bottom-up modelling approaches in energy demand modelling and DSM especially focused on their relationship with consumer activities and behaviours. The findings indicate that important consumer factors are usually oversimplified and understudied. To sum up, the literature review highlights the following findings:

- (1) The connection between the indoor loads and the EV charging loads was usually neglected. This connection is derived from consumers' cohesive daily activity profiles and represented by the overlapping load periods and flexible time ranges of the two profiles. For example, the end time of EV travel trips at home is typically the start time of both uncontrolled EV charging and indoor electricity consumption. However, due to the lack of simultaneous data on EV charging, indoor activities and residential loads in the same context, indoor load profiles and EV charging load profiles are usually studied separately in energy demand modelling and DSM.
- (2) The influential factors of activity-derived load have not been fully considered in energy demand modelling and DSM research. In the literature, activity load

was usually set as a constant depending on the activity type. However, other influential factors such as season, date, activity start time, energy price, household characteristics and the interaction between simultaneous activities were neglected.

- (3) Additional research is required to guide the energy demand models in terms of collecting influential factors, selecting optimal algorithms, and determining the historical window of features. Specifically, the activity data from surveys and recorders are important to understand how electricity is consumed by consumers. Meanwhile, ML-based energy demand models that rely on extensive meter data have gained increasing attention. Whether survey-based activity data adds value to the ML-based energy demand modelling remains a question.
- (4) The consumers' adaptation of activities in DSM is oversimplified. Researchers have studied consumers' willingness to participate in DSM and their preference for comfort and energy tariffs (Aloise-Young et al., 2021; Hille, Weber & Brosch, 2019; Sundt, Rehdanz & Meyerhoff, 2020). Meanwhile, the rescheduling of activity within flexible ranges is usually taken for granted based on the rational consumer hypothesis considering monetary expenditure. However, consumers in DSM usually adapt activity schedules to pursue individual benefits considering various influential factors such as the price level, the activity start times and socio-demographics.

These four limitations identified from the literature review underpin the four objectives of this PhD research. The next chapter introduces the datasets employed in this PhD research and subsequent chapters present frameworks to bridge the above gaps, covering the major processes in energy demand modelling and DSM.

Chapter 3

DATASETS

3.1 Overview

The datasets used in this PhD research can be categorised into two groups based on the data collection methods and purposes. The first group is secondary data which includes household electricity consumption, activity schedules, travel demand survey and appliance usage. These datasets serve as fundamental inputs and validation for the establishment of energy demand models and DSM models. What is more, they offer the opportunity to study the connection between indoor activities and travel patterns, as well as the connection between indoor activities and electricity consumption. The second group is primary data collected from a stated preference survey to understand the behaviours of adapting activities in response to time-of-use (ToU) tariffs in DSM. Most datasets are used multiple times throughout the PhD research and thus are introduced in advance in this chapter.

3.2 Secondary data

3.2.1 Project METER

Project METER (<https://www.energy-use.org/>) recruited UK households from 2016 to 2018 to record simultaneous time-use data and household electricity consumption measurements. This project provides the main dataset for Objectives A, B and C in Chapters 4 to 6 to establish energy demand models and DSM models. For each household in project METER, indoor activities, outdoor travel behaviours and electricity consumption records were collected on the same date. As a result, the real connection between these three types of records, which this PhD research intends to explore, is preserved. An overview of the data collection process is presented in this subsection, with more extensive details available in the literature (Grünewald & Diakonova, 2018; Grünewald et al., 2017). The data processing methods for each objective in this thesis will be demonstrated in the corresponding chapter to fit specific research models and purposes.

Project METER recruited over 200 UK households via radio, the Internet, and through campaigns at selected community events. The chance to win the cash equivalent of a year's worth of electricity was offered as a reward to motivate participation (Grünwald & Diakonova, 2018). In the data sample, high-income households with solar photovoltaics (PV) and electric vehicles (EV) were overrepresented as shown in Table 3.1. Particularly, participating households are more likely to live in the rural areas around Oxford, UK according to the recruitment methods and following analysis of travel patterns. The rural lifestyle may result in more frequent trip-making behaviours and flexible work schedules, which may contribute to higher EV charging demand and greater indoor activity flexibility. Consequently, the research based on the METER dataset needs further validation using larger and more representative datasets.

Table 3.1 Socio-demographics of the METER dataset and national figures
(Grünwald & Diakonova, 2018)

Feature	Group	METER dataset [%]	National [%]
Home	Ownership	85	64
Income	<15000	6	19
	<25000	13	22
	<35000	9	16
	<50000	21	17
	>50000	51	27
Occupants	1-2	57	64
	3-4	37	30
	>4	2	7
Age	Under 18	26	23
	19-50	47	44
	Over 50	24	35
Appliances	PV	14	4
	Electric Vehicle	4	0.4
	Washing machine/dryer	99	97
	Dishwasher	51	45

Recruited households provided socio-demographic information during the registration and received a parcel with a self-administered current clamp, a purpose-built device integrated with an activity recording mobile application and an instruction booklet. The survey date was chosen by the participants from 3 randomly assigned dates. The electricity monitoring and activity recording started at 5 pm and lasted about 30 hours to cover typical energy-intensive periods between 5 pm and 7 pm twice. Each household member aged 8 and above was encouraged to record activities, which created

the possibility to explore the impact of collective activities on household-level load profiles.

Electricity consumption was recorded every second by the current clamp installed under the main electricity meter. Then the electricity records were downsampled to mean values every 1 minute and 10 minutes. Activities were reported through the recording mobile application by selecting choices in six steps: activity, time, location, other people, enjoyment and edit (Grünewald et al., 2017). The last step “edit” allows participants to add more details about activities such as the particular nature of the activity (e.g., hot or cold meal) and a prompt for appliances that may have been in use (Grünewald & Diakonova, 2018).

Compared with conventional time-use survey data, the METER dataset has the following distinct features:

- (1) While time-use datasets are popular in activity modelling and energy demand modelling, simultaneous electricity consumption data is rare. The novelty of the METER dataset that it contains both time-use and electricity consumption data contributes to three research topics in this PhD research. In Chapter 4, the impact of EV charging loads on the residential load profiles is estimated accurately with real travel patterns and load profiles. In Chapter 5, residential load profile generation models based on real indoor activity records and corresponding electricity consumption are built. In addition, the contribution of these two types of input is analysed. Similarly, in Chapter 6, DSM models are established based on the real activity profiles in this dataset to provide an accurate estimation of the potential for improvement.
- (2) Unlike conventional time-use data where activities are recorded by one participant per household, Project METER recruits multiple participants per household, enabling the exploration of the collective activity impact. Household-level load profiles can also be aligned with all household members’ activities.
- (3) Activities were reported through mobile applications in Project METER. On the one hand, the start time of activities was recorded at the minute level, unlike the conventional approach of recording activities in each time slot. In addition, this recording method is “activity-driven” and multiple activities can be reported at

the same time slot to represent simultaneous activities so that activities do not have to be recorded as primary or secondary as in conventional time-use surveys. On the other hand, the energy-relevant details of activities were reported. This unique reporting method has both advantages and disadvantages for energy demand modelling. Activity-related details and exact start times provide rich information for accurate energy demand models. Simultaneous activities can also be estimated without the limitation of time slots and activity numbers, facilitating the understanding of their impact on energy consumption. However, the absence of activity end times poses challenges in estimating activity durations.

3.2.2 London Travel Demand Survey (LTDS)

LTDS is a continuous travel patterns and habits survey carried out each year in randomly selected households across the London area. LTDS provides real travel patterns such as travel speed, departure and arrival times to estimate the electricity consumption of EVs in Chapters 4 and 6. One fundamental premise in the use of LTDS data is that trips with EVs will share similar patterns to all the vehicle trips in the LTDS. This PhD research uses one of the latest versions of the LTDS that was conducted in 2018-2019.

LTDS records information on households, individuals, trips and vehicles through three kinds of questionnaires: household, individual and trip. The household questionnaires present basic demographic information and household characteristics such as income, housing tenure and vehicle ownership. Individual questionnaires record personal demographics and travel-related information, including working status and the frequency of using transport modes. Trip sheets provide details of all trips undertaken on a designated travel day, such as trip purposes, modes used, start and end times of trips, and the locations of trip origins and destinations (Transport for London, 2010).

3.2.3 The Household Energy Survey (HES, UK)

The UK Household Energy Survey (HES) selected 250 owner-occupied households across England by Ipsos MORI and monitored their electricity consumption at the appliance level (<https://www.gov.uk/government/collections/household-electricity-survey>). The HES dataset is 55 noptimi in Chapter 4 to estimate the electricity consumption of appliances. Among the households in HES, 26 households were

monitored from May 2010 to July 2011, referred to as “one-year households”, and the remaining 224 households were monitored for one month in the year, referred to as “one-month households”. The number of appliances monitored in each household was between 13 and 85. The HES dataset was one of the most detailed monitoring of electricity use ever carried out in the UK.

At the beginning of the HES project, electricians visited participating households to install the monitoring equipment. The electricity consumption of appliances was recorded every 2 minutes for “one-month households” and every 10 minutes for “one-year households”. Approximately one month later the equipment in “one-month households” was uninstalled. About six months later the data in the “one-year households” was downloaded and the equipment was reset to record every 2 minutes for another six months (UK Data Archive, 2011). Therefore, the HES dataset contains three profiles with different time intervals, household numbers and monitoring periods: (a) one-month monitoring with 2-minute intervals in 224 households, (b) half-year monitoring with 2-minute intervals in 26 households, (c) one-year monitoring with 10-minute intervals in 26 households. The last two profiles (b) and (c) overlap in the latter half of 2010 and were used in this PhD research to encompass a longer monitoring period and include as many households as possible.

3.2.4 Car parking records in a Singapore estate

Car parking records of a residential estate in Singapore are obtained to analyse the real parking patterns in Chapter 6. This estate has seven residential blocks accommodating approximately 889 units, along with a multi-story car park (MSCP) holding about 524 registered season parking permits. The parking events characterized by features such as the in-vehicle unit (IU) number, arrival times and departure times were recorded by electric traffic barriers at the entrance and exit of this estate. The IU number is a unique identifier of vehicles for paying the parking fee. The data processing and analysis will be shown in Chapter 6. After the data processing steps, 67310 parking records remained across 81 days from Jun 28, 2022, to Oct 05, 2022.

3.2.5 UK Time Use Survey

UK Time Use Survey (UK TUS) 2014-2015 recruited 4741 households across the UK to record their daily activities (Morris et al., 2016). Participants were instructed to complete two 24-hour (from 4 am to 4 am) surveys with 10-minute slots on a weekday

and a weekend day respectively (Gershuny & Sullivan, 2017). This TUS includes primary and secondary activities, locations of activities, presence of companions during the activities, level of enjoyment and the devices used. Household files and individual files are also provided with socio-demographic information.

3.3 Primary data

3.3.1 Stated preference survey for demand-side management (DSM-SP)

A stated preference (SP) survey for demand-side management (DSM-SP) was designed to collect consumers' choice of adapting activities in hypothetical situations when electricity prices change. The survey protocol was approved by the Science, Engineering and Technology Research Ethics Committee (SETREC) and a simplified version of the protocol is presented in Appendix 2. The results were used in Chapter 7 to build choice models and study the influential factors of these adaptation behaviours. The findings are used to estimate consumers' real reactions to price signals in DSM and guide the design of time-of-use electricity tariffs.

Although small-scale DSM has been implemented around the world, behaviours of activity adaptation have rarely been recorded and studied in detail. Consequently, the SP survey is an alternative way to obtain data about choices in activity adaptation. SP surveys have been widely used in travel behaviour research to identify responses to choice situations that are not revealed in the real world (David A. Hensher, 1994). According to the literature review, the SP survey and choice model is seldom employed to study activity adaptation in the domain of DSM, making this PhD research one of the first to introduce them to this domain.

This DSM-SP survey collects data such as the activity adaptation choices, current electricity tariffs, activity schedules, socio-demographic features and attitudes toward energy conservation of participants. The sequence of sections in the survey after the introduction and screening questions is shown in Figure 3.1. Participants are sequentially questioned about their current activity schedules and electricity tariffs, choices in hypothetical situations of activity adaptation, attitudes toward energy conservation and socio-demographics. Socio-demographic questions are placed at the end of the survey to mitigate the reluctance to provide personal information, by fostering familiarity and accumulating sunk costs throughout the survey. This DSM-SP survey was distributed to residents in the UK through a market research company

PanelBase in April 2023 and the processed dataset encompasses 1333 replies. Details of the survey design and data collection will be demonstrated in Section 7.2.

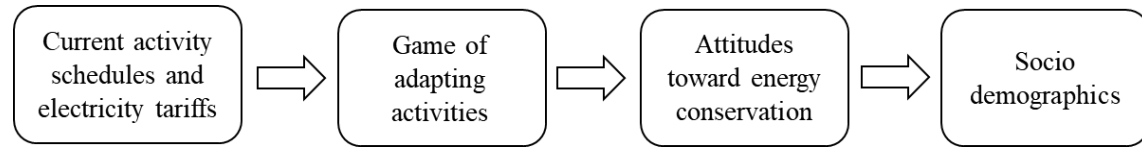


Figure 3.1 Structure of the DSM-SP survey

3.4 Summary

This chapter introduces the six main datasets used in this PhD research and their collection methods. The main data fields and intended usage of these datasets are listed below.

Table 3.2 Summary of datasets

Group	Name	Main data fields	Intended usage
Secondary data	Project METER	(1) Electricity consumption (2) Activity records (3) Weather (4) Electricity tariffs (5) Socio-demographics	Build energy demand models and DSM models
	London Travel Demand Survey (LTDS)	Trip records with arrival and departure times, travel speed, travel mileage and travel purposes.	Estimate travel patterns and the electricity consumption of EVs
	The Household Energy Survey (HES, UK)	Electricity consumption profiles of appliances	Estimate load profiles based on appliance usage
	Car parking records in a Singapore estate	Car parking records with arrival and departure times and IU number	Explore travel and parking patterns
	UK Time Use Survey (UK TUS)	Activity records	Explore activity schedules
Primary data	State preference survey	(1) Choice about adapting activities in response to ToU tariffs in DSM (2) Current activity schedules and electricity tariffs (3) Attitudes towards energy conservation (4) Socio-demographics	Study consumers' choices in response to ToU tariffs

Chapter 4

COORDINATED EV AND INDOOR LOAD GENERATION BASED ON CONVERSION FACTORS

4.1 Overview

A manuscript adapted based on the contents of this chapter has been submitted to Transportation Research Board Annual Meeting 2024¹.

Load profile generation models are pivotal to energy demand modelling and demand-side management (DSM) by providing daily electricity consumption profiles based on human activities. In recent years, the increasing residential electric vehicle (EV) charging demand, associated with the growth of private EV ownership, has been a focus in residential load profile generation. As consumers simultaneously schedule indoor activities and outdoor travel, their cohesive activity profiles lead to coordinated indoor load and EV charging load profiles. However, these two types of load profiles are often generated separately in the literature. Therefore, this chapter builds a load profile generation framework that considers the connection between indoor activities and travel patterns in the residential sector to provide coordinated electricity consumption profiles.

EVs have been promoted worldwide to mitigate the reliance on fossil energy and reduce carbon emissions. Additionally, EVs can serve as energy storage systems in the grid through vehicle-to-grid technology. However, uncontrolled EV charging can drastically increase electricity demand and cause adverse effects on the grid such as large load variations, high peak load and power quality degradation (Al-Ogaili et al., 2019). Especially in the residential grid, the preferred EV charging time often overlaps with the residential peak load periods (Mousavi Agah & Abbasi, 2012; Muratori, 2018). Therefore, the impact analysis of short-period EV charging loads is crucial for both the

¹ Wang, H., Guo, F. & Sivakumar, A. (2023) Impact analysis of residential EV charging based on coordinated load profile generation. Manuscript submitted for presentation.

design of DSM and the stable efficient residential grid. The label “short-period” indicates that the usage of EVs is modelled within the scale of a few days (Daina, Sivakumar & Polak, 2017). A common method to undertake this impact analysis is through load profile generation models with indicators such as peak load, total electricity consumption and voltage (Dubey & Santoso, 2015; Leemput et al., 2014; Chen et al., 2020; Pablo Carvallo et al., 2021). Section 2.2 reviews the generation models for indoor household loads and EV charging loads in the literature. The literature reveals that data accessibility remains a significant challenge as obtaining real data on EV charging loads and indoor residential loads in the same context is difficult. Consequently, EV charging loads and indoor residential loads are usually estimated based on separate datasets, ignoring the connection between them.

To bridge the aforementioned gap, this chapter presents a framework to generate coordinated load profiles including the EV charging loads and the household appliance loads. The impacts of generated EV charging loads on meter-recorded household indoor loads are analysed across three charging scenarios. Additionally, the generated household appliance loads are validated against the meter-recorded household indoor loads. The METER dataset (see Section 3.2.1) provides simultaneous time-use survey (TUS) data and meter records for the framework in this chapter. This METER dataset recorded real outdoor travel behaviours and indoor occupant behaviours from the same individuals, enabling the framework to capture the connection between them. London Travel Demand Survey (LTDS) (see Section 3.2.2) and the Household Energy Survey (HES) dataset (see Section 3.2.3) offer driving parameters and the load patterns of appliances respectively to estimate EV charging loads and household appliance loads. In the cleaned version of the METER dataset, only 14 households (7%) possess EVs. In addition, their departure and arrival times at home show no significant difference from those of households with non-EVs, potentially due to the limited sample size. Therefore, to simulate the scenario after full vehicle electrification, it is assumed that EVs maintain the same travel patterns (e.g., arrival and departure time) as conventional (i.e. non-electric) residential vehicles in the study area. The contributions of this chapter include:

- (1) A load profile generation framework built to simulate a coordinated residential electricity consumption profile, capturing the connection between travel activities, indoor activities and electricity consumption.

- (2) Impact analysis of the EV charging loads based on cohesive activity profiles and recorded household load profiles. Three charging scenarios are tested and compared based on real travel activities.
- (3) Validation of the aggregated household appliance load profiles that are generated by the proposed models against meter-recorded indoor load profiles. The advantages and disadvantages of indoor load generation models based on activity profiles and conversion factors are discussed.

The remainder of this chapter is organized as follows. Section 4.2 presents a brief description of the data processing steps. Section 4.3 explains the proposed framework in detail. Section 4.4 shows the model results and validation. Section 4.5 discusses the limitation of the framework and Section 4.6 concludes this chapter.

4.2 Data processing steps

The details of the METER dataset have been introduced in Section 2.2.1. In summary, the METER dataset recorded the simultaneous activity profiles and electricity consumption profiles for about 30 hours per household across over 200 UK households from 2016 to 2018. The following data processing steps aim to improve the quality of household activity profiles and load profiles in the METER dataset.

(1) Step 1: General quality

The research team of Project METER designed a feature “quality” for activity profiles and load profiles to evaluate the extent of errors and missing data. For activity profiles, “quality” is the number of activities reported. For load profiles, “quality” means the number of hours for which every 10-minute average load is 20 watts or above. In this study, households that have activity profiles with “quality” below 6 or load profiles with “quality” below 26 were excluded as advised by the research team of Project METER.

(2) Step 2: Missing values and outliers

Missing values in the recorded load profiles were interpolated by the previous valid records to maintain continuity. While extremely high loads could be derived from the usage of high electricity-consuming appliances such as washing machines and water heaters, extremely low loads are abnormal due to the existence of baseload from

“always-on” appliances. Therefore, electricity records below the lower bound of the 1.5 IQR rule were replaced with the low bound (Equation (4.1)).

$$lb = Q_1 - 1.5 IQR \quad (4.1)$$

$$ub = Q_3 + 1.5 IQR \quad (4.2)$$

where lb is the lower bound, ub is the upper bound, Q_1 is the 25th percentile, Q_3 is the 75th percentile, and the inter-quartile range (IQR) is the difference between the 25th and 75th percentiles.

(3) Step 3: Moving average

The moving average method was applied to the recorded load profile. Grünewald & Diakonova (2018) demonstrated that individuals reported 67% of their activities within 10 minutes accuracy in Project METER. Pawlak et al. (2021) argued that setting $S=20$ in a standard moving average method in the METER dataset should cover approximately 95% of the true start time of activities. Therefore, the moving average method was also adopted (Equation (4.3)).

$$\hat{L}_t = \frac{1}{2(S+1)} \sum_{s=0}^S (L_{t+s} + L_{t-s}) \quad (4.3)$$

where $\hat{L}_t$ is the average load at time t , and L_t is the meter-recorded load at time t .

4.3 Methodology

Figure 4.1 shows the proposed framework for estimating coordinated load profiles that include the charging loads of EVs and the loads of household appliances.

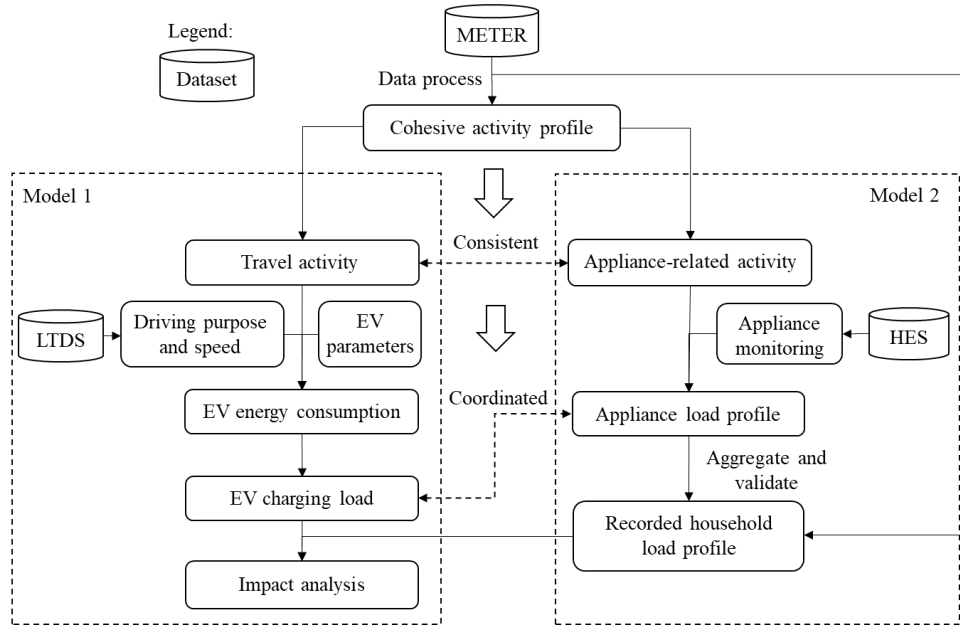


Figure 4.1 Proposed framework.

This framework contains two parts:

(1) Model 1 — EV charging load generation and impact analysis

The electricity consumption of EVs is estimated based on travel activities from the METER dataset, driving parameters from the LTDS dataset and typical EV parameters. Three typical EV charging scenarios are designed to generate residential EV charging load profiles. Finally, the EV charging load profiles and meter-recorded household indoor load profiles are combined to analyse the impact of EVs.

(2) Model 2 — Household appliance load generation and validation

Load profiles of household appliances are generated based on indoor activities in the METER dataset and the monitored load profiles of appliances in the HES dataset. For each household, generated appliance load profiles are aggregated as the indoor household load profile. The result is then validated against meter-recorded household load profiles in the METER dataset.

This framework provides a structured approach to generating coordinated residential load profiles by utilising cohesive activity profiles alongside two separate models for indoor loads and EV charging loads. This framework can be extended to analyse the impact of EVs and provide input to DSM. In addition, the two separate models integrated in the framework can be adapted to improve the modelling accuracy as discussed in Section 4.5 and Chapter 5.

4.3.1 Model 1 – EV charging load estimation and impact analysis

To estimate EV charging load profiles, this model assumes that households in the METER dataset will replace their current vehicles with one type of EV and retain the same travel patterns. Tesla Model 3 is the most common generic model of Ultra Low Emission Vehicles registered for the first time in the UK for the year ending December 2020 (Department for Transport, 2021). Therefore, the parameters of Tesla Model 3 are used in this model including a battery capacity of 40 kWh and a power consumption efficiency of 14.9 kWh/100km. The energy consumption of EVs is estimated based on travel mileage and energy efficiency as shown in Equations (4.4) and (4.5) (Ho et al., 2014; Haque, Kurukuru & Khan, 2019; Duan et al., 2018).

$$E_m = D_m \times e \quad (4.4)$$

$$D_m = v_m \times T_m \quad (4.5)$$

where E_m is the EV electricity consumption (kWh) of trip m , D_m is the driving distance (km) of trip m , e is the energy efficiency (kWh/km) of the EV, v_m is the average driving speed (km/minute) of trips that are in the LTDS and have the same purpose as the trip m , and T_m is the driving duration (minute) of the trip m .

Driving duration T_i and driving purposes j are extracted from the METER dataset. The start time was recorded in the METER dataset and the end time was set as the start time of the next activity. Abnormal driving durations are observed due to unrecorded activities between adjacent trips. Therefore, the driving durations exceeding the upper bound of the 1.5 IQR rule (Equation (4.2)) are replaced by the average duration of trips with the same driving purpose. Multiple trips that are recorded by different household members, starting within 5 minutes and with more than one person involved are marked as one collective trip. Five driving purposes, i.e., work, leisure, shopping, escort and others, are determined based on activity types recorded in the METER dataset and are consistent with the driving purposes in the LTDS dataset. The driving speed of trips in the METER dataset is set as the average speed of car trips with the same purpose in the LTDS dataset.

This model also assumes that EVs are fully charged in the beginning and will be charged once they arrive at the allowed charging points, which is also known as uncontrolled charging. In addition, the State of Charge (SOC) of EVs is calculated

whenever EVs arrive at charging points to check whether the previous trip can be completed. The charging process ends when another trip starts or when the EV is fully charged. The calculation of SOC is shown in Equations (4.6)-(4.7).

$$S_{n,m-end}^{EV} = S_{n,m-start}^{EV} - E_m / E^{EV,max} \quad (4.6)$$

$$S_{n,t}^{EV} = S_{n,t-1}^{EV} + L_{m,t}^{EV} / E^{EV,max}, \quad S_{n,t}^{EV} \leq 1 \quad t=0, 1, 2 \dots d \quad (4.7)$$

where $S_{n,t}^{EV}$ is the SOC of EV n at time t , $S_{n,m-start}^{EV}$ and $S_{n,m-end}^{EV}$ are the SOC of EV n at the start and end time of its trip m respectively, $E^{EV,max}$ is the battery capacity of EVs, and d is the end time of EV charging.

Three charging scenarios are designed as described below and an example is shown in Figure 4.2. The maximum charging rate is the typical household charging rate of 3.7 kW (Fischer et al., 2019; Sun, Neumann & Harrison, 2020).

- (1) Scenario 1: EVs can only be charged at home and the charging rate always reaches the maximum.
- (2) Scenario 2: EVs can be charged at home, in workplaces and public places. The charging rate always reaches the maximum.
- (3) Scenario 3: EV can only be charged at home but the charging rate is limited to make sure no new peak load occurs in the meter-recorded household load profile (Equation (4.8)).

$$L_t^{EV} + L_t^{indoor} \leq L_{peak}^{indoor} \quad \forall t \in T \quad (4.8)$$

where L_t^{EV} is the EV charging load at time t , L_t^{indoor} is the recorded household load at time t , L_{peak}^{indoor} is the peak load in the recorded household load profile, and T is the whole period of the recorded load profile.

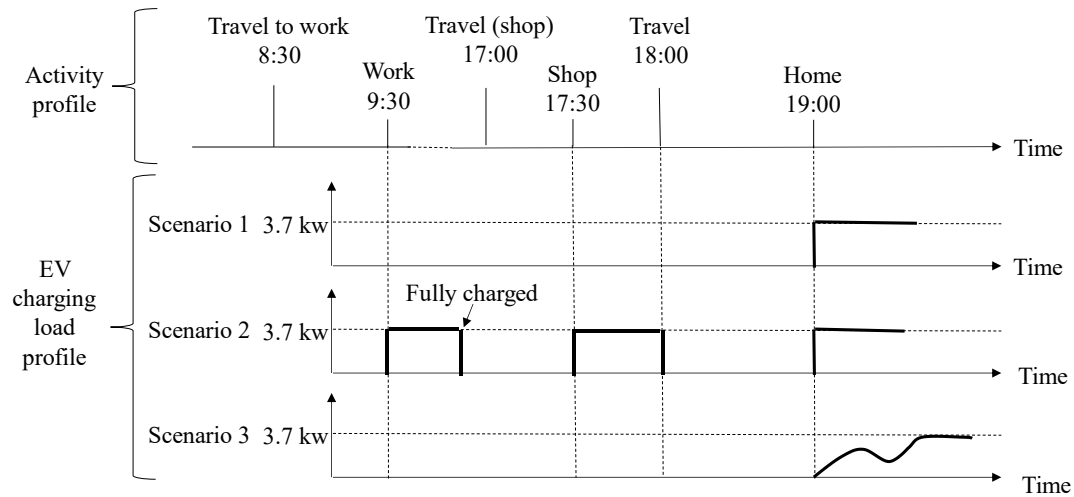


Figure 4.2 EV charging scenarios.

Based on these three charging scenarios, three EV charging load profiles at home are estimated. Finally, the impact analysis is conducted by integrating the estimated EV charging loads and meter-recorded household loads in the METER dataset at the household and aggregated levels.

4.3.2 Model 2 – Load generation for household appliances

This load generation model for household appliances is developed considering the model used in (Widén et al., 2009) and the particularity of the METER dataset. This model assumes appliances and indoor activities in the METER dataset have the same constant load patterns extracted from the HES. Although in reality, the load of appliances usually fluctuates during operation, this fluctuation is not captured by the TUS data and is thus simplified in this chapter. The generated load of household appliances is aggregated and then validated against meter-recorded household load profiles in the METER dataset. To facilitate the validation, the estimated and recorded load profiles should be associated with the same activity profiles. Thus, popular probabilistic activity generation models, e.g., the Markov chain model, are not used.

The differences between the model used in this chapter and the model in (Widén et al., 2009) lie in the time interval, the operating duration and the load patterns of appliances. Widén et al. (2009) generated hourly load profiles based on a standard TUS dataset which provides the end time of activities. In addition, the constant load patterns and operating durations of appliances were obtained through product tests. On the contrary, in this model, the end time of activities was not available. Additionally, the operating

duration and the load patterns were extracted from the HES dataset with 1-minute intervals.

The appliance load generation model grouped appliances into two categories: (1) activity-unrelated appliances and (2) activity-related appliances.

(1) Activity-unrelated appliances

Activity-unrelated appliances include “Cold appliances”, e.g., fridge, freezer, and “Lighting” because their operation is rarely recorded in TUS data (Stankovic et al., 2015). In this chapter, the load profiles of activity-unrelated appliances are assigned as the average daily load profiles of similar appliances in the HES dataset. In addition, these load profiles are modified by the seasonal factors provided by the HES dataset corresponding to the surveyed dates in the METER dataset.

(2) Activity-related appliances

Activity-related appliances are those with clear activity records when participants use them. Their load profiles are generated based on the average load and average operating durations of similar appliances from the HES dataset. The most frequent activities at home in the METER dataset are summarised into 11 appliance groups. These appliance groups, associated activity names in the METER dataset and associated appliances in the HES dataset are shown in Table 4.1. Participants in Project METER can edit the activity name through the mobile application described in Section 3.2.1 to add more details. As a result, each appliance group can be associated with multiple activity names.

Table 4.1 Activities and appliances in the METER dataset and HES dataset

Appliance group	Activity names in the METER dataset	Appliances in the HES dataset
Kettle	‘Kettle’, ‘kettle’, ‘Appliances Kettle’, ‘Boil kettle’, ‘Toast and tea’, ‘Hot drink’, ‘Food drink hot’, ‘Kettle (end)’	Kettle 1, kettle 2
Cook	‘Prepare hot meal’, ‘Prepare meal’, ‘Start cooking supper’, ‘Eating hot meal’, ‘Eating’, ‘Eat’, ‘Food’, ‘Food or drink’, ‘Food eat hot’, ‘Breakfast’, ‘Having breakfast’, ‘Eating breakfast’	Cooking (groups)
Hob	‘Cook on hob’, ‘Hob’, ‘Cook on hob (end)’	Hob 1, hob 2
Oven	‘Oven’, ‘Oven (end)’	Oven 1, oven 2

TV	'Watching TV', 'TV', 'Appliances TV', 'Leisure TV TV', 'Leisure TV', 'TV with the cat', 'Tv', 'Watching TV (end)', 'TV (end)'	TV watching(groups)
Information and communication technology (ICT) products	'Computer', 'Internet', 'Computer games', 'Appliances Computer', 'Screen time (tablet)', 'Leisure TV Laptop', 'Work (computer)', 'Charging laptop', 'Emails on laptop', 'Computer use', 'Screen time (laptop)', 'Internet (computer)', 'Computer (end)', 'Internet (end)', 'Computer games (end)', 'screen time'	ICT(groups)
Shower	'Shower', 'Care wash shower', 'Shower my daughter', 'Shower (end)'	Shower 1, shower 2
Dishwasher	'Dish washer', 'Dishwasher', 'Appliances Dish washer', 'Set dishwasher to run later', 'Dishwasher will run for 2 hours 38 minutes', 'Dishwasher loading'	Dishwasher 1
Washing machine	'Appliances Washing machine', 'Set washing machine to run later', 'Washing machine', 'Washine machine', 'Washing machine (end)'	Washing/drying machine 1, washing machine 1, washing/drying machine 2
Microwave	'Appliances Microwave', 'Microwave', 'Microwave (end)'	Microwave 1, microwave 2
Toaster	'Toaster', 'Appliances Toaster', 'Toast', 'Toast and tea', 'Toaster (end)'	Toaster 1, toaster 2

The process of extracting the average loads (in watts) and the average operating durations (in minutes) from load profiles of associated appliances in the HES dataset is shown in Figure 4.3.

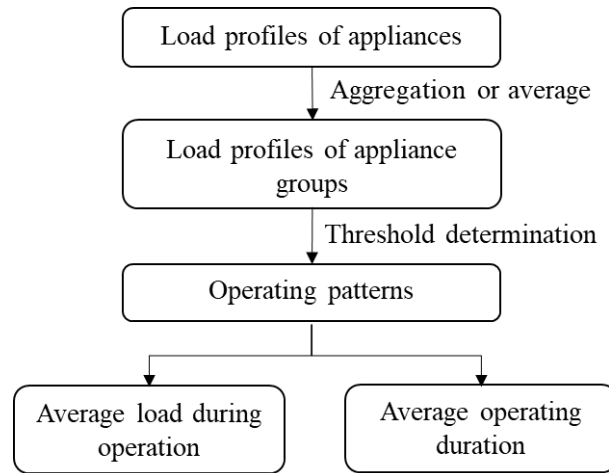


Figure 4.3 Load pattern extraction

In the HES dataset, if an appliance group, e.g., “Cook” and “ICT”, associates with multiple kinds of appliances and these appliances are usually operated together, their load profiles in a household are aggregated. Otherwise, their load profiles are averaged as they are usually used separately, such as “Kettle”. In addition, the appliance group “Cook” is further divided into “making breakfast”, “making lunch” and “making dinner” according to the start time of activities to capture the differences between them. To calculate the operating patterns from the continuous monitoring in the HES dataset, a threshold is set for each appliance group based on its average load, the value distribution and load profiles. Examples of how the thresholds can be determined will be shown in Section 4.4.2. The operating duration in this model is defined as a period where the load exceeds the threshold for over 10 minutes. Then the average load during the operation and the average operating duration are calculated.

To estimate the missing end time of activities in the METER dataset, this chapter further classifies the activity-related appliances into two categories: (a) appliance group associated with uninterrupted activities whose operating duration is assigned as the average operating duration from the HES dataset. Examples include “Kettle”, “Washing machine” and “Dishwasher”; (b) appliance group associated with interruptible activities whose end time is assigned as the earlier timing between the end time after an average duration extracted from the HES dataset, and the start time of the next activity in the profile. Examples include “TV”, “ICT” and “Shower”. This load assignment method can represent the overlap of activities, which is not typically considered in previous load generation models. During the load assignment of activity-related appliances, other influential factors such as the ownership of electrical

appliances and collective activities are also considered. A load assignment example is shown in Figure 4.4.

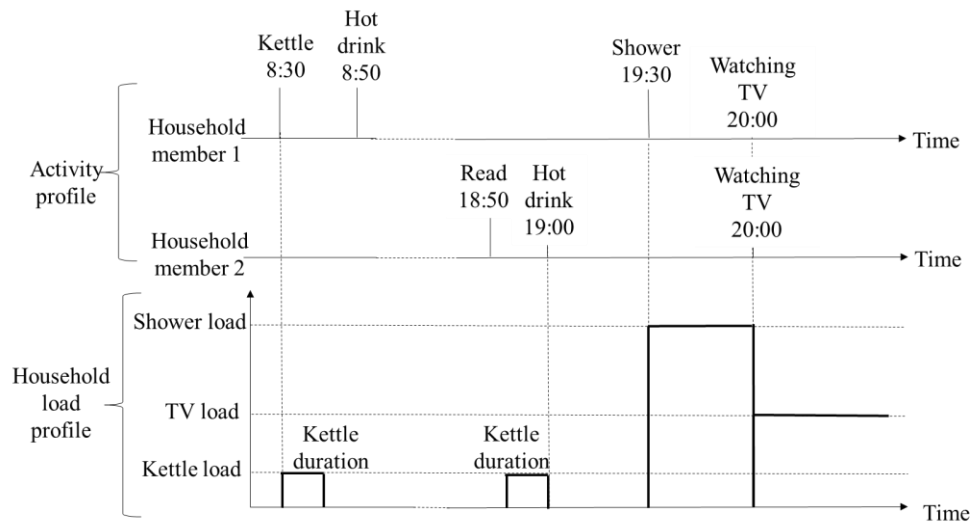


Figure 4.4 Household load assignment

4.4 Results and discussion

4.4.1 Results of Model 1 EV charging load generation

After applying the data processing steps, 201 households remained and 100 households among them performed at least one car trip during the surveyed period. Household load profiles with 1-minute intervals in the METER dataset were selected for impact analysis to align with the minute-level trip records in the LTDS and minute-level generated EV charging loads. The impacts of EV charging loads under three charging scenarios are shown in Table 4.2.

Table 4.2 The results of impact analysis under three charging scenarios

Items	Scenario1: charging at home	Scenario2: charging at multiple points	Scenario3: charging at home with limited rates
SOC mean	86.5%	88.4%	86.0%
SOC standard deviation (std)	12.3	11.3	12.7
SOC minimum	10.4%	10.4%	8.6%
SOC 25 th percentile	81.3%	84.6%	81.3%
SOC 50 th percentile	90.1%	92.2%	89.8%
SOC 75 th percentile	95.0%	95.8%	95.0%
Increment in the aggregated profile of all households			
Total electricity consumption	19.0%	16.1%	12.9%

Peak load	35.0%	31.9%	14.9%
Increment in the aggregated profile of households with car trips			
Total electricity consumption	49.8%	42.6%	31.2%
Peak load	181.9%	170.2%	0%

The results show that most trips can be completed by EVs with a SOC above 25% when EVs arrive at charging points, whatever the charging scenario is. The only exception as the “SOC minimum” in Table 4.2 is a household with 495 minutes of driving and only 30 minutes of charging in the middle. This probably indicates a long trip or unrecorded activities occurring midway. The results of mean and percentile SOC show that compared with a unique charging point at home (Scenario 1), multiple charging points at work and public places (Scenario 2) can increase the overall SOC. Conversely, charging at home with limited charging rates (Scenario 3) decreases the overall SOC.

For all households, the EV charging loads increase the total electricity consumption by 12.9% to 19.0% across different charging scenarios. In addition, the EV charging loads increase peak load by 14.9% to 35.0%. Scenario 2 can reduce the load burden on the residential grid as EVs can be charged outside of the residential area. Scenario 3 causes an even smaller load increment due to limited charging rates but at the cost of lower SOC.

The average daily load profiles of all households with and without EVs under three charging scenarios are shown in Figure 4.5. This figure shows that the uncontrolled EV charging loads (red line) cause a clear increment in the peak load. In addition, Scenario 3 with charging control (blue line) is more efficient in mitigating the peak load increment, especially during the evening peak time. In contrast, Scenario 2 (green line), which extends charging places to public and workplaces, slightly reduces the peak load increment. The main reason could be the fewer recorded stops (0.79 stops per household with car trips) at public and workplaces, despite the long staying time (174.26 minutes per household with car trips), in the METER dataset. Note that this travel pattern is likely to be specific to the METER dataset as discussed in Section 4.6.

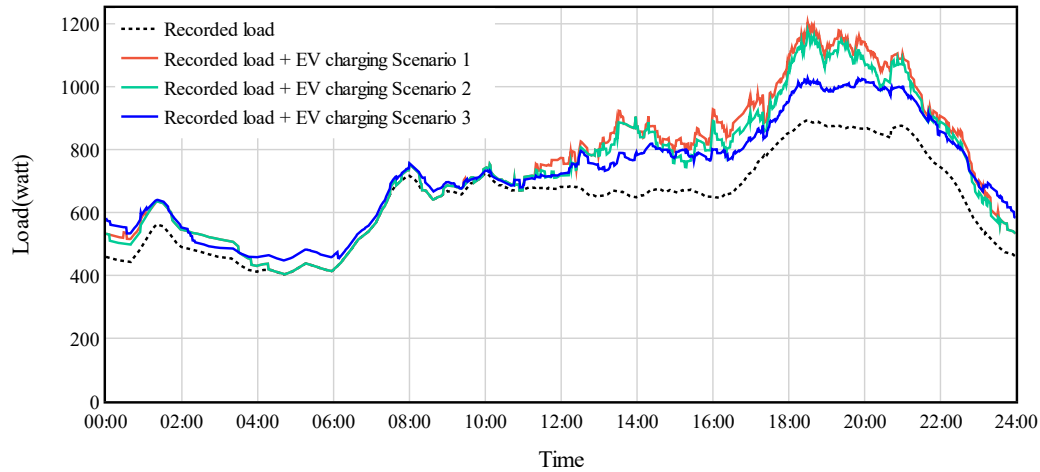


Figure 4.5 Average daily household load profiles under different scenarios.

Table 4.2 also shows that, for households with car trips, the total electricity consumption increment is 31.2% to 49.8% across charging scenarios. Scenario 1 with free charging may cause a huge increase of 181.9% in the peak load of these households with car trips. However, Scenario 3, a simple rule-based limitation on EV charging power rate, can mitigate the increment in peak load without much influence on SOC and EV usage. The load profile of a random household is shown in Figure 4.6 as an example where Scenario 3 (blue line) reduces the charging rates and requires a longer charging period.

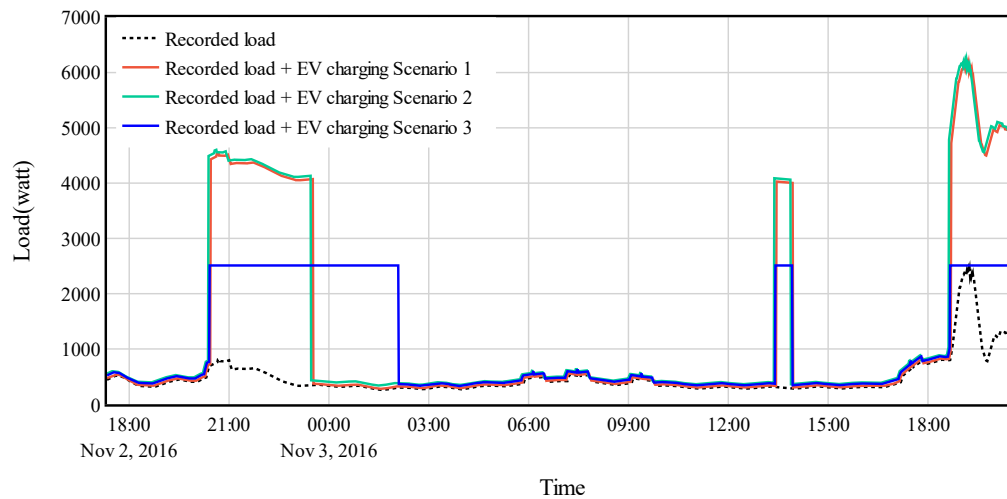


Figure 4.6 A household load profile (HouseholdID: 8048).

4.4.2 Results of Model 2 household appliance load generation

In this household appliance load generation model, both electricity consumption records in the METER dataset and the load monitoring profiles in the HES dataset are

at 10-minute intervals. After the data processing described in Section 4.2, about 199 households in the METER dataset remained.

For activity-unrelated appliance groups “Cold appliance” and “Lighting”, the average daily load profiles of these groups of 239 households in HES are shown in Figure 4.7, where each line represents a household. The obvious outlying load profiles were removed and then the average daily household load profiles were generated in Figure 4.8. The average “Lighting” load profile shows two obvious peaks in the morning and night while the average “Cold appliance” load profile is flat.

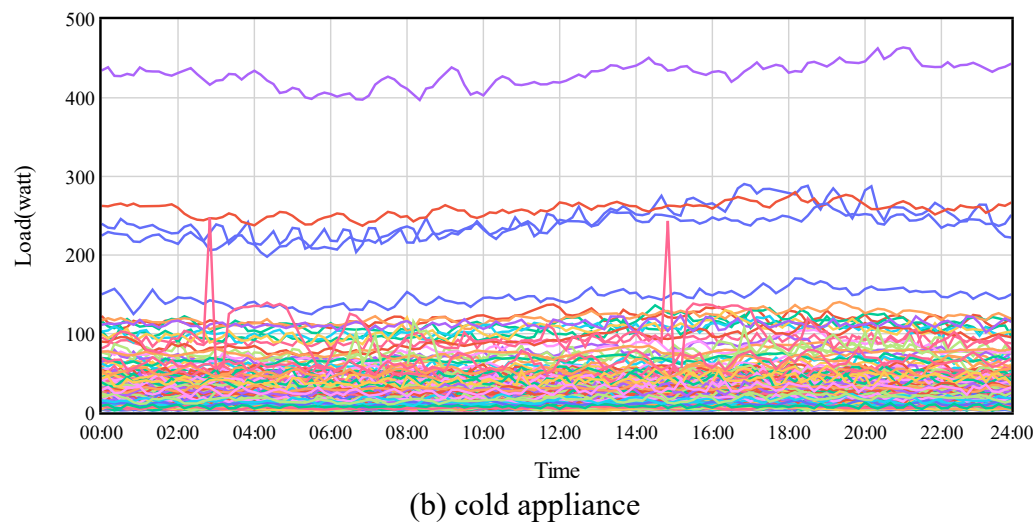
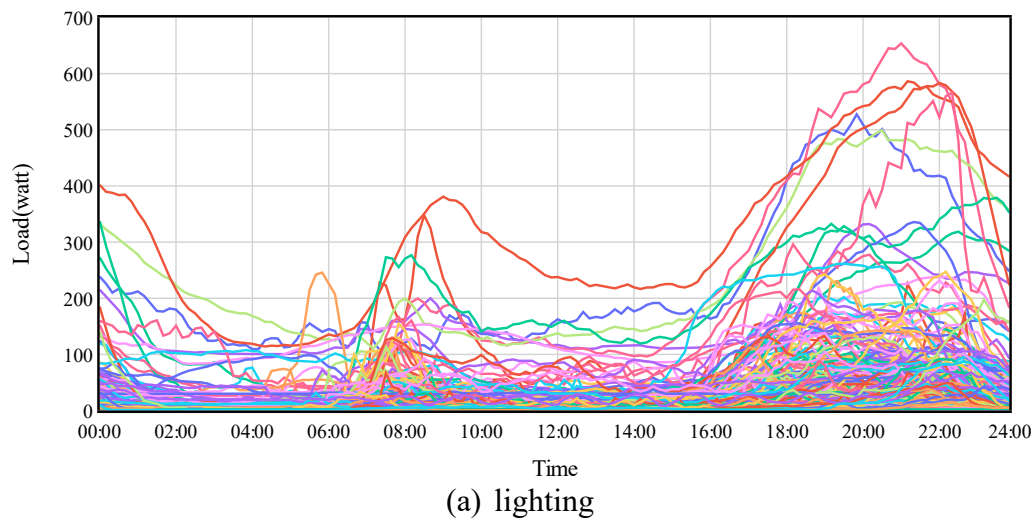
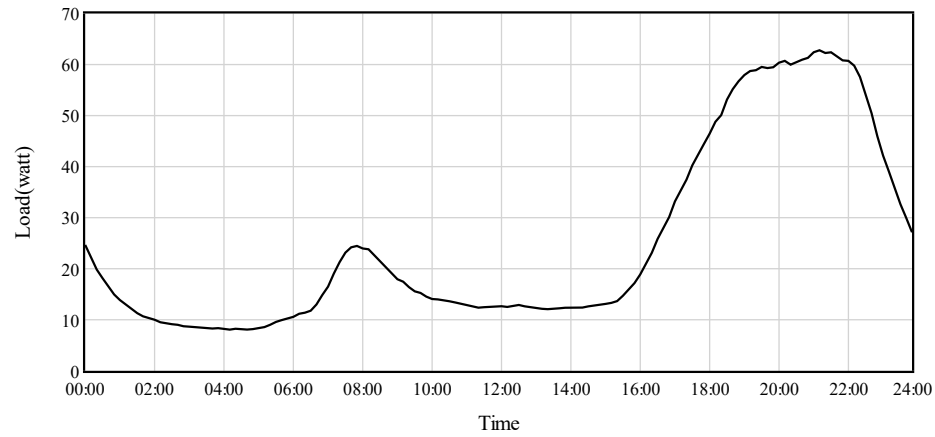
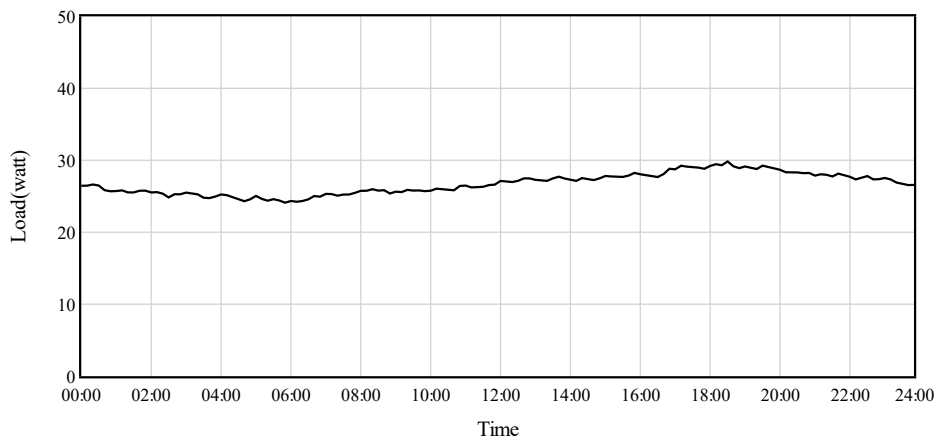


Figure 4.7 The household average daily load profiles



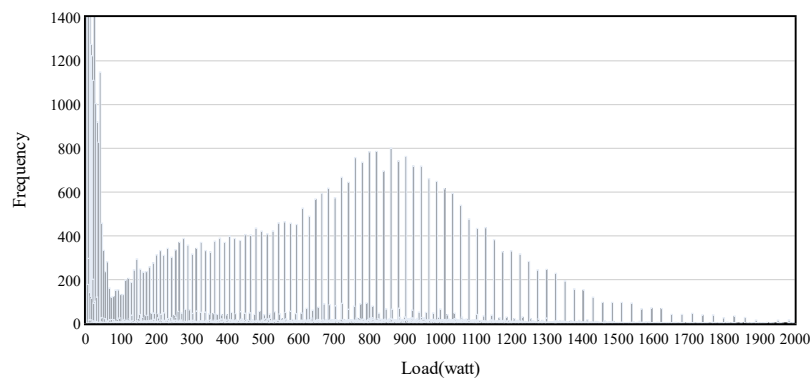
(a) lighting



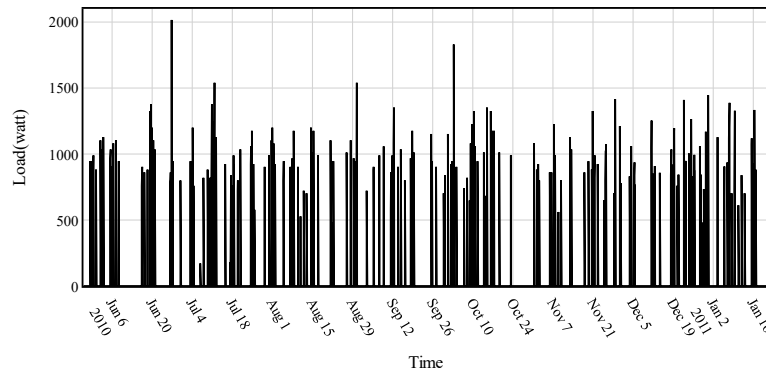
(b) cold appliance

Figure 4.8 Average daily household load profile

For activity-related appliances, the process of determining the threshold is shown with examples of “Kettle” and “TV”. As described in Section 4.3.2, the threshold was determined based on the average load, the value distribution and load profiles. In the HES dataset, The average load of appliance group “Kettle” is 31.24 watts. The frequency distribution of load values of “Kettle” is shown in Figure 4.9 (a) and the “Kettle” load profile from a random household is shown in Figure 4.9 (b).



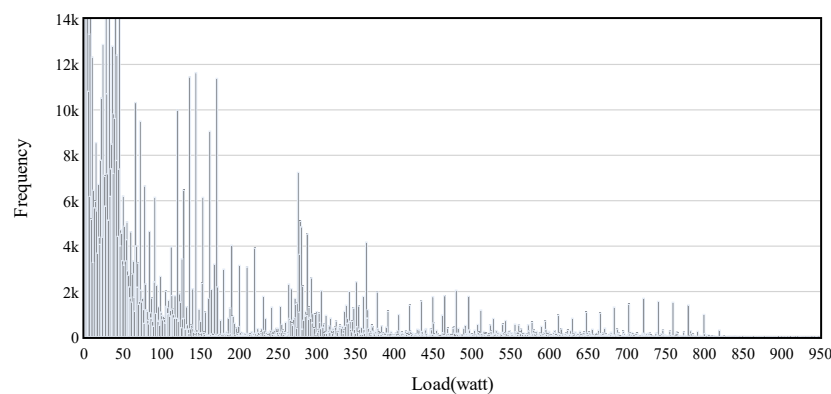
(a) frequencies of load values



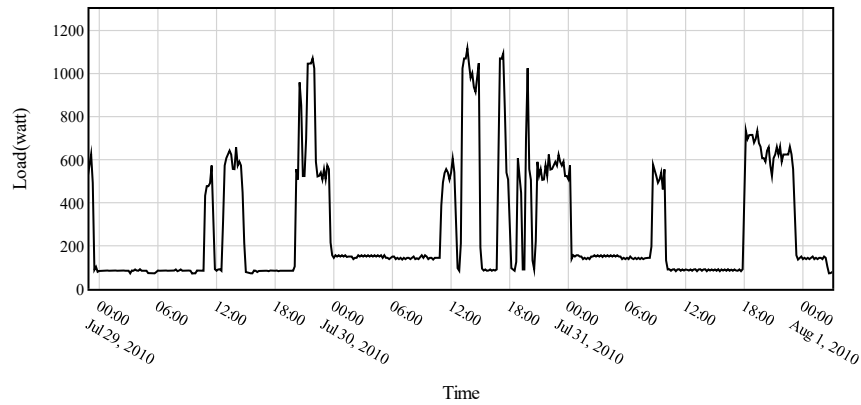
(b) a household load profile (HouseholdID: 103013)

Figure 4.9. Kettle load.

Figure 4.9 (a) suggests that appliance group “Kettle” has two operation modes with loads approximately at 0 and 900 watts respectively. Figure 4.9 (b) and the load profiles of other households indicate the absence of standby kettle loads. Therefore, the threshold for “Kettle” was set as 72 watts, corresponding to the low point between the two operation modes in Figure 4.9 (a). When the frequency distribution of load values does not show obvious peaks, the threshold was set as the larger one between the average load and the standby load. For example, in the HES dataset, the average load of “TV” is 61.66 watts and the frequency distribution of “TV” load values is shown in Figure 4.10 (a). The “TV” load profile with the highest standby load is shown in Figure 4.10 (b). Therefore, given the absence of peaks in the frequency distribution of loads, the threshold of “TV” was set as 160 watts which is about the highest standby load. Notably, the results of household appliance load generation are not sensitive to the threshold since most loads of appliances are much larger than the threshold as shown in Figure 4.9 (a) and Figure 4.10 (a). Table 4.3 presents the calculated average operation loads and average operating durations for appliance groups.



(a) frequencies of load values



(b) a household load profile (HouseholdID: 103014)

Figure 4.10 TV load.

Table 4.3 The average loads and operating durations of appliance groups

Appliance group		Threshold load (watt)	Average load during operation (watt)	Average operating duration (minute)
Kettle		72	634.05	17
Cook	Making Breakfast (0~10 am)	56	454.94	24
	Making Lunch (10 am~3 pm)	56	336.65	27
	Making Dinner (3 pm~12 am)	56	742.77	29
TV		160	373.22	20
ICT		175	297.75	24
Shower		32	2542.51	25
Oven		110	931.32	57
Hob		120	739.56	33
Dishwasher		312	1730.54	38
Washing machine		480	1658.48	21
Microwave		114	569.49	16
Toaster		210	460.87	13

Based on the parameters in Table 4.3 and activity profiles in the METER dataset, household appliance load profiles were generated and aggregated at 10-minute intervals to be the household load profiles. The results are compared with meter-recorded household load profiles. Since recorded load profiles in the METER dataset do not contain 0 value, this model used mean absolute percentage error (MAPE) and Normalized Variation Factor (NVF) as shown in Equations (4.7) and (4.8) (Widén et

al., 2009) to evaluate the performance of load profile generation models. Smaller MAPE and NVF mean better performance.

$$MAPE = \frac{100}{n} * \sum_{i=1}^n |(y_i - \hat{y}_i) / y_i| \quad (4.9)$$

$$NVF = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n((1/n) \sum_{i=1}^n y_i)^2} \quad (4.10)$$

where, $\hat{y}_i$ is the recorded load records (watt) at time i , y_i is the generated load records (watt) at time i , n is the length of the load profiles.

The results in Table 4.4 show that the performance of Model 2 household appliance load generation varies greatly between households.

Table 4.4 Performance of household appliance load generation model

	Load profiles per household			Average household daily load profile
	Minimum	Maximum	Average	
MAPE	41%	152%	76.9%	75.9%
NVF	0.38	8.53	1.07	0.55

The comparison between the average recorded and generated daily household load profiles is shown in Figure 4.11. This figure presents that the generated load profile captures the fluctuation of load during the day but is about 470 watts lower than the recorded load profile. The potential sources of errors are analysed below.

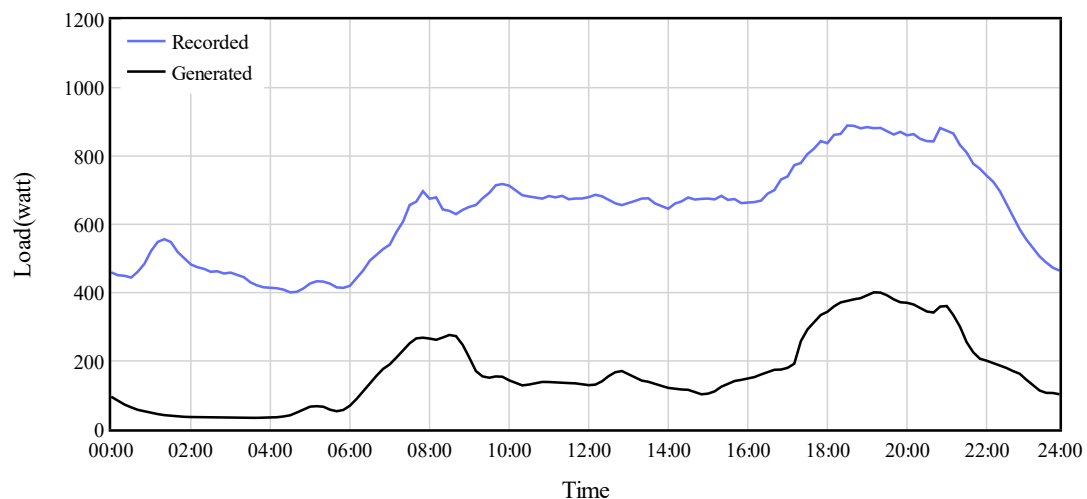


Figure 4.11 The average recorded and generated daily household load profiles.

- (1) The main source of errors probably is the unknown activity-unrelated appliances and “always-on” loads that are active throughout the day, such as

thermostats and the standby load of TV and ICT. These “always-on” loads can not be estimated based on the TUS data. Consequently, the generated load profile is the lower of the two parallel curves with the recorded load profile above it. One example is shown in Figure 4.12 where the generated load profile captures the period of peak loads but underestimates the level of standby loads.

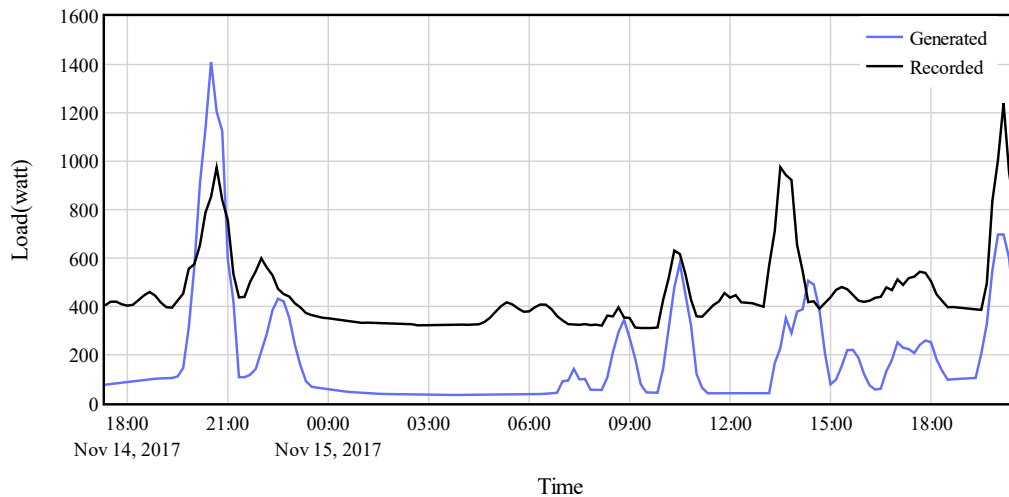


Figure 4.12 Unknown “always-on” loads in a household (HouseholdID: 8646)

(2) Another source of errors is unrecorded activities or unconsidered activity-related appliances. This error source results in the comparison between peaks in the recorded load profiles and low flat curves in the generated load profiles during the same period. For example, the household in Figure 4.13 did not record any activities during the two peak load periods at 23:20 on 13 Jan 2017 and 11:50 on 14 Jan 2017.

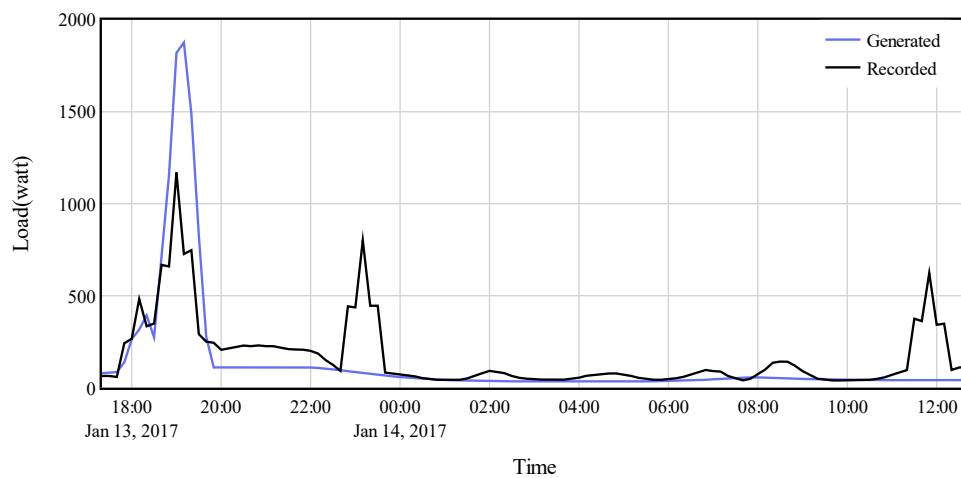


Figure 4.13 Unrecorded activities (HouseholdID: 8023)

In addition, the household in Figure 4.14 recorded an activity “Vacuum cleaning” at 18:32, 14 Apr 2017, but the usage of vacuums is not considered in this model due to their infrequent occurrence in the METER dataset.

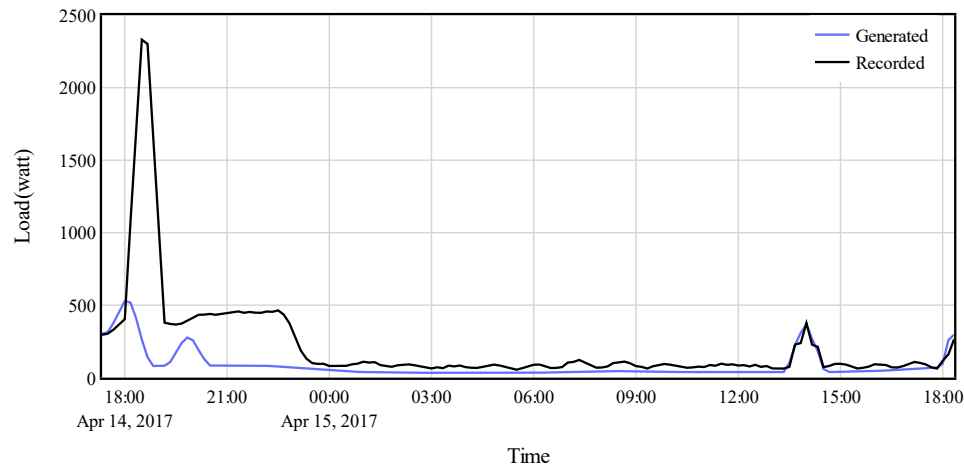


Figure 4.14 Unconsidered activity-related appliance (HouseholdID: 8171)

- (3) The last source of errors comes from the uncertainty of the dataset, the load patterns of appliances and the model assumptions. The METER dataset does not record the end times of activities and thus this load profile generation model estimates the end time as described in Section 4.3.2. However, the actual duration of activities may differ from these estimates. For example, in Figure 4.14, one member of the household started the activity of “Watching TV” at 19:46:13 on 14 Apr 2017. This activity probably ended at 22:40 according to the drop in load profiles at that time. This activity lasted for about 180 minutes and this duration is much longer than the average operating duration of watching TV. Furthermore, this chapter utilised the average load of appliances extracted from the HES dataset while appliances can have different power rates and load patterns. For example, a washing machine may have different load patterns for the working stage “wash”, “rinse” and “dry” (Pipattanasomporn et al., 2014) which may be treated as three operations in this study.

4.5 Discussion

This bottom-up load profile generation framework estimates coordinated EV charging loads and indoor appliance loads based on cohesive activity profiles. Applying this framework to other cases is easy since the parameters from the LTDS dataset and the HES dataset can be referenced from the literature and TUS data is quite common around

the world. Future research in policy-making, building simulation and DSM can be explored based on this coordinated load profile generation framework.

Model 1 analyses the impact of EV charging loads on residential load profiles at both the household and aggregated levels based on real indoor electricity consumption profiles and travel patterns. The utilisation of cohesive activity profiles not only captures the connection between EV charging loads and indoor loads but also retains the heterogeneity of households. In addition, this EV charging load generation model shows the ability to evaluate EV charging scenarios based on the location of charging points owing to the recorded travel destinations in the TUS data. The uncertainties of Model 1 include travel patterns, the parameters of EVs and charging rates. Travel demand surveys from the same participants in the TUS may improve the reliability of EV travel patterns. In addition, different EV parameters need to be tested.

Model 2 generates indoor load profiles by aggregating loads of appliances. Widén et al. (2009) tested the usefulness of TUS data in modelling household load profiles. Their paper shows that this bottom-up method with conversion factors reproduces the qualitative features of measured hourly load profiles with a small validation dataset of 5 households. This type of model is easy to apply and can predict future energy use by updating the parameters and datasets according to technique improvement and behaviour change. In contrast, this chapter builds a similar model and tests its performance in the larger METER dataset which encompasses load profiles with 10-minute intervals from about 200 households. The results show that although the fluctuation of average daily load profiles can be reproduced, this type of model based on conversion factors needs to be improved in many aspects. For example, identified sources of errors include unknown “always-on” loads, unrecorded or unconsidered activities, and model uncertainty. A simple correction method would be to introduce a constant load for activity-unrelated appliances or to scale the model parameters (Widén et al., 2009). In addition, detailed household surveys which include the end time of activities, as well as the ownership and power rate of appliances can provide more information about the load patterns.

4.6 Summary

This chapter presents a load profile generation framework to estimate electricity consumption profiles in the residential network based on TUS data. Two types of

coordinated load profiles, i.e., household appliance loads and EV charging loads, are generated based on cohesive activity profiles, and thus the connections between indoor activities, outdoor travel behaviours and electricity consumption are explored. The results are analysed to highlight the impacts of EV charging loads on residential loads such as the increment in overall electricity consumption and peak loads. In addition, the advantages of smart charging scenarios are tested. The results of household appliance load generation models with conversion factors are validated and discussed. The main conclusions of this chapter include:

- (1) In aligning with the literature (Zou et al., 2023; Jia & Long, 2020), this chapter demonstrates that uncontrolled EV charging behaviours can significantly increase residential peak loads. Researchers have designed advanced EV charging control approaches with technologies such as energy storage systems and Vehicle-to-Grid (V2G) to mitigate this impact on the grid (Xu & Huang, 2022; Das et al., 2021). Similarly, the experiment with real activity profiles in this chapter shows simple rule-based limitations on EV charging power rate can also mitigate the increment in peak loads without substantially influencing SOC and EV usage. This reveals the great potential of DSM with the smart charging of EVs.
- (2) The validation of the designed model shows that survey-based load generation with conversion factors can capture the fluctuation of average daily load profiles but at lower value levels. Literature that utilised similar models with fine-tuned conversion factors in a small dataset resulted in satisfactory estimations of residential load profiles (Widén et al., 2009). However, the validation in this chapter with a relatively larger dataset suggests that constant load patterns of appliances may be insufficient to capture the heterogeneity of indoor activities, appliances and households.

A few limitations of this chapter are acknowledged. Firstly, the results may not be general as the METER dataset is not representative of the general population. About 200 households, mainly in rural areas, were recruited in Project METER. The monitoring period of 30 hours per household is also limited. The rural lifestyle may result in more frequent trip-making behaviours and flexible work schedules. Consequently, the results need further validation using larger datasets.

Secondly, the estimation of the EV charging loads in Model 2 was not validated against real data due to the scarcity of coordinated travel patterns and charging records of EVs. In addition, the parameters and assumptions of EVs adopted from the literature, such as the battery capacity, charging rates and travel patterns, are somewhat outdated, requiring updating and further analysis. For example, the Tesla V3 Superchargers in public places support peak charging rates of up to 250 kW per car and the Tesla Universal Wall Connector at home can provide charging rates of up to 11.5 kW. Consequently, EVs need a short charging time to be fully charged for about two days' worth of trips and do not need to stay connected to the grid continuously while parking at home.

Furthermore, the limitations of the load generation model with conversion factors are revealed. For example, the constant load patterns of appliances may not accurately represent diverse appliance power. In addition, the "always-on" loads and other load influential factors are not captured. The next chapter will introduce indoor load profile generation models based on machine learning algorithms to address these limitations and take more influential factors into account, such as the start time of activity, weather, and the interaction between simultaneous activities.

Chapter 5

LOAD PROFILE GENERATION BASED ON METER RECORDS AND ACTIVITY SURVEYS WITH MACHINE LEARNING MODELS

5.1 Overview

The contents of this chapter are contained in the journal paper: Wang, H., Pawlak, J., Faghieh Imani, A., Guo, F. & Sivakumar, A. (2023) When does it pay off to use electricity demand data with rich information about households and their activities? A comparative machine learning approach to demand modelling. *Energy and Buildings*. 295, 113292. Doi:10.1016/j.enbuild.2023.113292.

An indoor load profile generation model was built based on constant conversion factors and appliance usage in Chapter 4. Although that model can capture the fluctuation of average daily load profiles, constant load patterns cannot capture the heterogeneity of indoor activities, appliances and households. Additionally, other influential factors such as the activity start times, weather, and the interaction between simultaneous activities are not considered. Therefore, this chapter aims to integrate these influential factors into load generation models using machine learning (ML) algorithms. The performance of six ML algorithms, i.e., Support Vector Regression (SVM), Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Light Gradient Boosting Machine (LightGBM), Random Forest (RF) and K-Nearest Neighbors (KNN), is compared through three groups of scenarios. The first group includes eight scenarios of “meter-based” and “survey-based” influential features. The second group explores the impact of four different historical time window widths, while the third group tests models in two train-test split methods. What is more, an appropriate methodology is designed to capture the temporal impact of indoor activities on the load profiles and represent the overlap and interaction of simultaneous activities.

The “meter-based” and “survey-based” approaches in load profile generation have been introduced in the literature review in Section 2.2.1. These two approaches rely on

meter-recorded electricity consumption and survey-recorded activity schedules respectively to generate load profiles. Because of their different requirements for data collection, these two paradigms are not necessarily easy to combine, which warrants the question of when one may be preferred over the other and whether they need to be combined despite the heavy data collection work required to source both datasets. A review paper by Grandjean, Adnot & Binet (2012) points out that survey-based models require simultaneous activity records and energy consumption measures. However, activity data is relatively sensitive and associated with privacy concerns, which increases the difficulty of long-term data collection. In the residential context, activity data are usually recorded through surveys or recorders, such as smartphones, among a large number of households. However, to avoid participant fatigue and discomfort, the activity recording usually covers a short period, such as a few days. In contrast, energy consumption data can be recorded by smart meters and sensors over a longer time, usually spanning months or years, with less disturbance to the participants compared with surveys. In other words, meter data collection can be time-consuming to guarantee the accuracy of the meter-based approach.

In addition to the activity type, various other influential features affect energy demand patterns and there is no ‘one size fits all’ method to select the most appropriate features. These influential features include socioeconomics, calendar features, weather and energy prices. Socioeconomic features (e.g., age and income) are usually used in the unified predictive model for multiple households as they can reflect the general energy consumption level and activity habits (Schirmer, Geiger & Mporas, 2021). Calendar features (e.g., the hour of day, the day of week and seasons) are related to occupancy schedules and activity profiles, which impact energy demand (Xu, Wang & Tang, 2019). Weather features tend to have a huge impact on heating and cooling energy consumption. Therefore, short-term weather forecasts and long-term climate change in energy demand modelling are popular topics (Xu, Wang & Tang, 2019; Lucas Segarra, Ramos Ruiz & Fernández Bandera, 2021; Ma & Yu, 2020). Energy price is a vital influencing factor of energy consumption and multiple energy tariffs (e.g., dynamic time-of-use, dToU) have been used in the real world to reshape load profiles (Dai & Zhao, 2020; Schofield et al., 2014). Although each of these features has been studied in the literature, their relative contributions to load profile generation have not been

compared in the same context. Therefore, an overall understanding of their contributions is necessary to guide efficient data collection and feature engineering.

Although an increasing number of ML algorithms have been introduced into prediction models in energy demand modelling, there has not been any discussion about the suitability of the various algorithms. Popular ML algorithms include Linear Regression (LR), Tree-based Algorithms, SVM, Neural Networks (NN) and Deep Learning (DL) (Zhang et al., 2021a). Although the performance of these algorithms largely depends on the data quality and sample size, the general agreement is that non-linear machine learning methods such as SVM, NN and DL tend to outperform LR when a large amount of data is available (Lusis et al., 2017; Shabbir et al., 2019; Amasyali & El-Gohary, 2021). Despite the intensive study of ML algorithms, research about how to build a proper input dataset is rare. For example, historical data is widely used as input but the width of the historical time window for features is usually arbitrarily decided. Another less discussed issue is how the train-test split impacts the model performance. Two common train-test split methods correspond to two specific application contexts. When the historical data of modelling targets are adequate, ML algorithms can train and test in the same context, referred to as the “within data source” split. On the contrary, when the modelling target has limited or no historical data, ML algorithms need to be trained in one context but applied in another context, referred to as the “between data sources” split. These different train-test split methods can be compared in one study to accurately evaluate the performance of ML algorithms in different application contexts.

To address the gaps discussed above, this chapter designs three groups of test scenarios and compares the performance of six ML algorithms in a multi-household residential context provided by the METER dataset. Specifically, the impact of eight sets of influential features, four different widths of historical time windows, and two train-test splits on ML-based energy demand models are analysed. Additionally, the advantages and disadvantages of survey-based and meter-based approaches are discussed based on the comparison results. ML algorithms compared include LightGBM, Random forest, ANN, SVM, KNN and LSTM. Influential factors considered include historical load records, household and individual attributes, appliance ownership, indoor activities, weather and energy tariffs (Pawlak, Imani & Sivakumar, 2021).

The remainder of this chapter is structured as follows. Section 5.2 covers data processing methods. Section 5.3 describes the modelling framework including ML models and the experimental setup. Section 5.4 presents the test results. Section 5.5 discusses the difference between the modelling approaches, the different performances of ML models, as well as the research limitations. Section 5.6 summarises this chapter.

5.2 Data processing

The data from Project METER underwent 8 steps of processing by Pawlak, Imani & Sivakumar (2021) to enrich the information and remove incomplete observations (Figure 5.1). Particularly, in step 4, approximate electricity price values were estimated based on the first part of the household postcode and the tariff names recorded in the METER dataset. The estimation methods include utilising the national average annual energy price data from consumer price indices for fuels from the Department for Energy Security and Net Zero (DESNZ, formerly Department for Business, Energy & Industrial Strategy BEIS) (DESNZ, 2023), available prices specific to the postcode from tariff comparison service UKPower (www.ukpower.co.uk) and online information about the prices associated with the recorded economy tariffs (Choose Ltd, 2023; Sedo, 2023). Despite potential inaccuracies arising from missing data, this method enriches the dataset with crucial details, including tariff names, potential peak and off-peak hours, and the associated electricity prices.

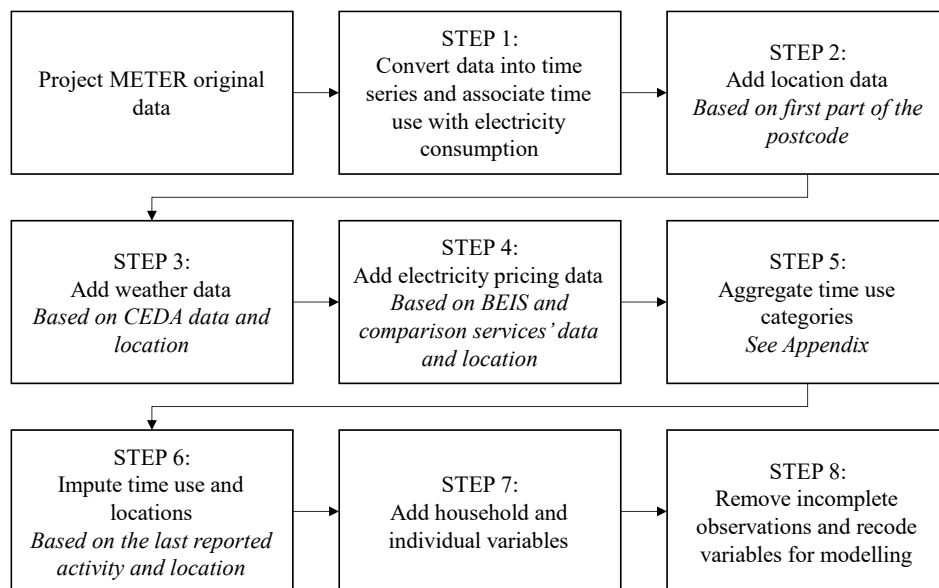


Figure 5.1 Data processing steps (Pawlak, Imani & Sivakumar, 2021)

This chapter adopted the same processing method and adjusted the following steps to enable its use for the ML models. In the METER dataset, the start time of activities rather than the activity status in each time slot are recorded at the 1-minute interval. This causes one substantial shortcoming that the end time of activities is absent and most time slots have no activity records. These sparse activity start times provide little information for the ML predictive models to capture the impact of indoor activities on energy consumption. In previous research based on the same dataset (Pawlak, Imani & Sivakumar, 2021), the time slots without activity records were imputed with the most recently reported activity. For example, the recorded start time of activity A was set as the missing end time of the former activity B. However, this imputation method may generate inaccurate estimations of end times. Some indoor activities, such as the usage of appliances, usually end when the appliance operation cycles end. In other words, the end time of the appliance operation cycle is not necessarily the time that the next activity starts. Therefore, the activity duration can be overestimated or underestimated. Moreover, consistent with most existing literature, this approach neglects the overlap of activities.

Instead of the imputation method, this chapter designs two features, “Peopleinvolved” and “TimeCredit”, for each activity type. “Peopleinvolved” was recorded by participants and shows how many people were involved in the activity. “TimeCredit” is designed to offset the sparsity of activity records, represent the temporal impact of indoor activities and explore the interactions between activities. The idea for “TimeCredit” is that activity, with its impact on electricity consumption, is more likely to happen and endure in the time slot approximate to the recorded start or end time. In other words, since the duration of this activity was not recorded, it is reasonable to assume the “survival” possibility of the activity, as well as the probability of affecting electricity consumption, decreases as the temporal distance from the recorded time increases. Consequently, for each activity type in the profile, “TimeCredit” first assigns a constant value to the recorded activity time slot. In most cases, this activity record signifies the start of an activity. Subsequently, the “TimeCredit” value decreases over the maximum duration of the corresponding activity. While sporadically the activity record signifies the end of an activity (e.g., activity records with the suffix “(end)”) and then the “TimeCredit” decreases retroactively over the same maximum duration. Without loss of generality, this constant value at the recorded activity time slot is set as 180 (minutes)

as the longest duration of common activities (Bissey, Jacques & Le Bunetel, 2017; Nazemi, Jafari & Zaidan, 2021).

An example of the “TimeCredit” for several indoor activities is shown in Figure 5.2. In summary, “TimeCredit”, denoted by $TC_{t,A}$, can be seen as the extent to which activity A is believed to happen or endure at time t based on the temporal distance between the recorded start/end time $\hat{t}$ of activity A and the time t . In addition, each type of electricity-consuming activity has its own “TimeCredit” feature and a time slot may have several non-zero “TimeCredit” values of different indoor activities. Therefore, these “TimeCredit” in the same slot can represent the simultaneous presence of multiple indoor activities and help the ML algorithm explore the interactions between them.

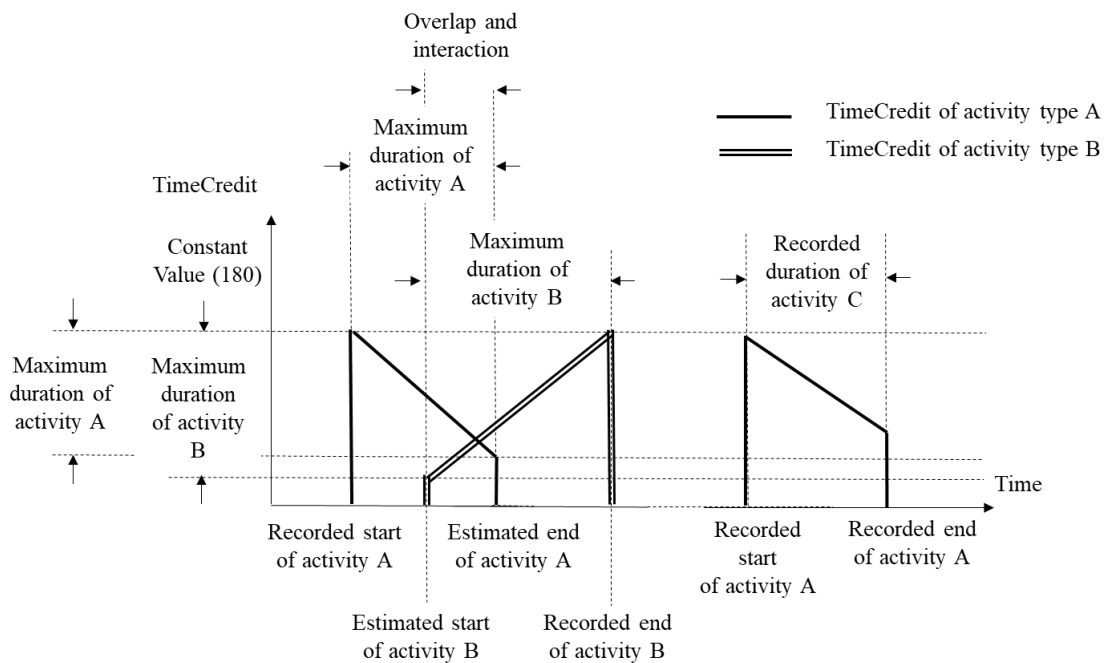


Figure 5.2 An example of “TimeCredit”

This chapter also adopts the moving average method from previous research based on Project METER as stated in Section 4.2. After all the data processing steps and the moving averaging of the energy consumption, 164 households remained and the 1-minute interval energy consumption records ranged from 1.8 Watts to 8302.5 Watts, with the observed mean of 659.6 Watts and the standard deviation (std) of 784.1 Watts. Figure 5.3 shows the histogram and density of energy consumption records after all the data processing is completed.

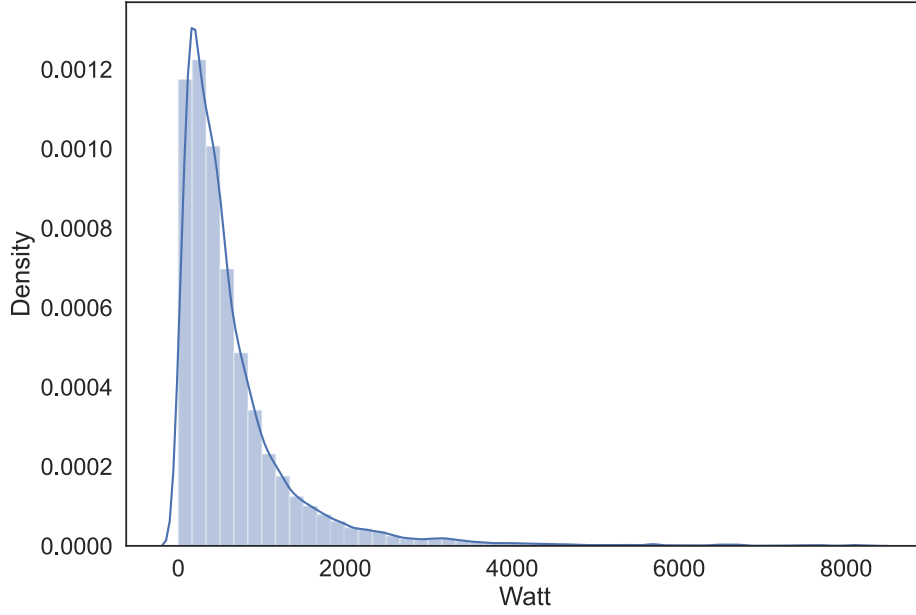


Figure 5.3 Histogram of electricity consumption records after processing

To facilitate the modelling with ML algorithms, categorical features, such as household type and income range, were processed into numeric features with the Pre-processing scheme Target Encoder (Micci-Barreca, 2001). Other numeric features, such as household size and room numbers, were normalised. Cyclical features, such as the minute of day, were encoded by their sine and cosine values Equation (5.1) (Tian, Li & Xue, 2021). By doing this, the time stamp 23:59 is very close to 00:00, as it should be.

$$\sin_{minute} = \sin\left(\frac{2\pi T_{minute}}{24 \times 60}\right), \cos_{minute} = \cos\left(\frac{2\pi T_{minute}}{24 \times 60}\right) \quad (5.1)$$

where T_{minute} is the minute of day. After the processing methods above, the input features are summarised in Appendix 1 and can be categorised into six main types: smart meter records, weather, energy tariff, household and individual attributes, appliance usage and general activity categories.

5.3 Research Methodology

5.3.1 Experimental setup

Energy demand models in the literature usually generate typical or random daily load profiles based on estimated daily activity schedules at 30-minute or 60-minute intervals. That kind of model suits certain applications well, such as the calculation of market energy prices in the whole market which is also updated at hourly or half-hourly intervals. However, it may not be appropriate for real-time application of energy

management systems and DSM (Shi et al., 2017; Elkazaz et al., 2020; Vermeer, Mouli & Bauer, 2020) where quick response is required and at the time of control the activity data for the next hours are not available. In addition, load profiles with finer granularity, such as 1-minute intervals, have a potentially high degree of variability, noise and missing values from a data perspective. Despite these challenges, smart or real-time energy control often necessitates load profiles with finer granularity to achieve more effective and prompt control.

Therefore, considering the issues above, the experiment in this chapter aims to predict 30-minute ahead household electricity consumption based on the 1-minute interval load profiles in the multi-household METER dataset. This experiment is dictated by the following factors. Firstly, only features in the historical time window are used as inputs to satisfy the requirement of real-time control. Secondly, the granularity of a 1-minute interval is used to capture the detailed demand fluctuation. Thirdly, to accommodate DSM with real-time prices in the wholesale electricity market, electricity consumption over the next 30 minutes needs to be estimated to match the update interval of real-time prices. Hence, the electricity demand 30 minutes ahead is selected as the prediction target without loss of generality. The developed models can be used to predict electricity consumption and generate load profiles for real-time or day-ahead DSM and smart electricity management. Three groups of scenarios are designed to investigate (a) Scenarios Group 1: the contributions of features, (b) Scenarios Group 2: the impact of the width of historical time windows, and (c) Scenarios Group 3: the impact of train-test splits. Figure 5.4 shows the flowchart of the tests. The results are analysed to determine effective methodologies for feature engineering and model selection to obtain accurate electricity consumption profiles in different scenarios.

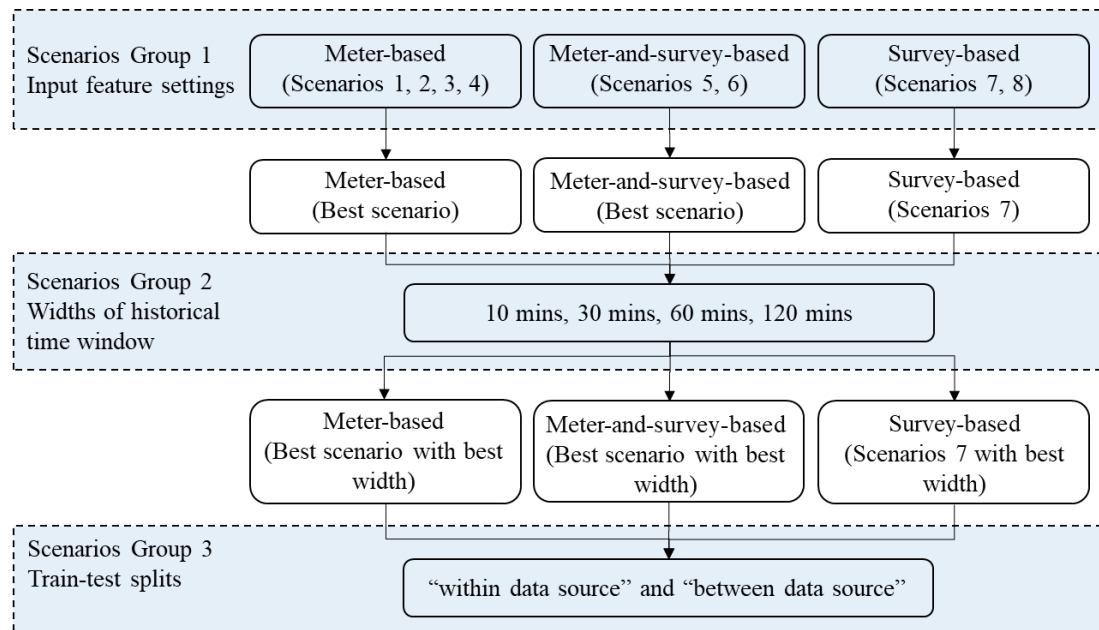


Figure 5.4 Flowchart of the tests

Group 1 contains eight scenarios, each reflecting a combination of input features. Then, models are categorised into meter-based, survey-based and meter-and-survey-based according to the feature combinations used (see Table 5.1). Scenarios 1 to 4 are meter-based models, where the prediction model uses smart meter records, with other energy-related features introduced one at a time, such as weather, energy tariff, household and individual attributes. Scenarios 5 and 6 are meter-and-survey-based models, which utilise both meter-related and survey-related features. Scenarios 7 and 8 are survey-based models with all features except for smart meter records. In addition, all scenarios contain general calendar features such as the time of day and the day of week. Kolmogorov–Smirnov test (K–S test) is used to assess the statistical significance of the difference between adjacent scenarios. The difference is considered to be significant when the resulting p-value is less than 0.05 (i.e., $p < 0.05$).

Table 5.1 Input feature settings in Group 1

Scenario		Meter-related features		Other energy-related features			Survey-related features	
Category	ID	Smart meter records	Statistics (Smart meter records)	Weather	Energy tariff	Household and individual attributes	Appliance usage	General activity categories
Meter-based	1	•						
	2	•		•				
	3	•		•	•			

	4	•		•	•	•		
Meter-and-survey-based	5	•		•	•	•	•	
	6	•		•	•	•	•	•
Survey-based	7			•	•	•	•	•
	8		•	•	•	•	•	•

Scenario 8 introduces “Statistics (Smart meter records)”, the statistical features of historical energy consumption records into Scenario 7. Scenario 8 aims to test whether statistical load features can improve the survey-based models in the absence of detailed load profiles. Typically used in load forecasting research, statistical load features often take various forms such as the loads at the same time on similar previous days and the average load of the previous day (Lusis et al., 2017). However, these common statistical features cannot be extracted from the METER dataset since each household was monitored for only 30 hours. To circumvent this, the statistical features of the whole monitoring period were added based on the assumption that statistical load features do not change greatly between days. These substitutional statistical features include the average, maximum, minimum, median, 25th percentile, 75th percentile and standard deviation of the smart meter records. Although at the risk of data leakage, we expect that Scenario 8 can exhibit the best improvement due to the addition of these statistical features.

Within Group 1, the dataset was split within households as the “within data source” train-test split method. In other words, the initial 80% and the remaining 20% of each household’s monitoring records were used as training and test sets respectively. For the prediction at each time slot, the electricity consumption record from 30 minutes after the current time t was the prediction target, with corresponding inputs of features within the historical time window before the current time slot t . As shown in Figure 5.5, k is the width of the historical time window and n is the temporal distance between the time of prediction target and current time t . The width of the historical time window, k , in Group 1 is 30 minutes.

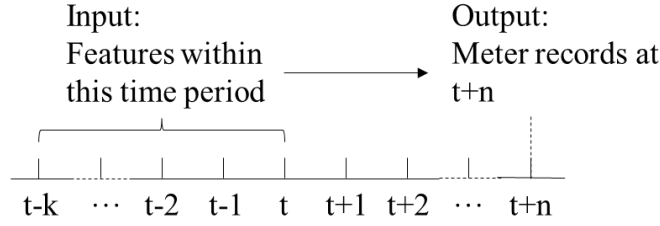


Figure 5.5 Historical time window

Group 2 tested four scenarios with different widths of the historical time window (k in Figure 5.5): 10, 30, 60 and 120 minutes. For each scenario in Group 2, three input feature settings derived from Group 1 were tested. Two of these three are settings with the best performance in each of the meter-based models (Scenarios 1 to 4, Group 1) and the meter-and-survey-based models (Scenarios 5 and 6, Group 1). The last one is the survey-based model Scenario 7 rather than Scenario 8 due to the concern of potential data leakage. The train-test split remains within households.

Group 3 investigated two train-test dataset split methods, “within data source” (as described in Groups 1 and 2) and “between data sources”. In the “between data sources” method, the train-test dataset was split across households employing a 5-fold cross-validation method. For each fold, 80% of households were selected with all their monitoring data designated as the training dataset. The data from the remaining 20% of households formed the test dataset. These two splits embody different application contexts depending on the availability of the historical data pertaining to the target households. The same three input feature settings in Group 2 were used and their corresponding widths of historical time windows were the ones with the best performance in Group 2.

All the groups and scenarios were trained and tested using Python’s statistical and machine learning toolbox.

5.3.2 Machine learning algorithms and performance metrics

A set of ML algorithms are tested in this chapter. Zhang et al. (2021) summarised nine main types of ML algorithms in building load prediction: (1) Linear Regression, (2) Support Vector Machine (SVM), (3) Neural Network (NN), (4) Deep Learning, (5) Tree-based Algorithms, (6) Hybrid, (7) Autoregressive methods, (8) fuzzy time-series model, and (9) Others. This chapter selects six typical regression models from these categories: Support Vector Regression (SVM), Artificial Neural Network (ANN), Long

Short-Term Memory (LSTM), Light Gradient Boosting Machine (LightGBM), Random Forest (RF) and K-Nearest Neighbors (KNN). These models are tuned by cross-fold validation and grid search methods to obtain the best performance. Linear regression models are not tested since multiple research shows that linear regression models usually perform worse in this context due to the nonlinearity of the relationship between energy consumption and influential factors (Lusis et al., 2017; Amasyali & El-Gohary, 2021). Instead, the lazy learning model KNN, which generalizes the data after a query is made, is used as the benchmark model. Features are scaled and then selected by F-value before training.

Root mean square error (RMSE), mean absolute percentage error (MAPE) and coefficient of variation (CV) are used as performance metrics to evaluate the model performance, as presented in Equations (5.2)–(5.4). Lower RMSE, MAPE and CV indicate better prediction performance and greater similarity between the predicted and actual energy consumption records. RMSE is the primary performance metric with the unit of Watt·minute or Watt as the interval is 1 minute. This smaller unit makes the RMSE in this chapter more than 1000% larger than that with a common unit kW·h in similar research. In addition, the 1-minute interval data may also result in a higher degree of variability and thus higher RMSE than the hourly data.

$$RMSE(\text{watt} \cdot \text{minute}) = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad (5.2)$$

$$MAPE(\%) = \frac{100}{n} \times \sum_{i=1}^n |(y_i - \hat{y}_i) / y_i| \quad (5.3)$$

$$CV(\%) = \frac{\sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}}}{\frac{1}{n} \sum_{i=1}^n y_i} \times 100 \quad (5.4)$$

where y_i is the true value, $\hat{y}_i$ is the predicted value and n is the number of forecasted targets.

5.4 Results

5.4.1 Group 1: Input feature settings

Table 5.2 summarises the prediction results of eight scenarios in Group 1. The best performance is achieved by LightGBM in meter-based Scenario 4 (RMSE: 463.36). LightGBM in meter-and-survey-based Scenarios 5 and 6 also reaches close

performance levels (RMSE: 464.83 and RMSE: 463.71 respectively). Although statistical features in Scenario 8 can slightly improve the survey-based Scenario 7, these two survey-based models do not perform as well as other models. The differences in results between adjacent scenarios caused by adding new features are significant as most p-values in the K–S test are less than 0.05.

Table 5.2 Results of input feature setting test (Group 1)

Scenario		Metrics	LightGBM	Random forest	ANN	SVM	KNN	LSTM
Meter-based	1	RMSE	500.35	512.17	500.67	581.21	549.90	549.72
		MAPE	136.89%	381.17%	273.94%	142.58%	406.79%	452.56%
		CV	64.79%	66.32%	64.83%	75.39%	71.21%	70.88%
	2	RMSE	502.05	513.42	501.96	582.48	554.15	585.46
		MAPE	150.06%	411.40%	268.66%	142.64%	435.06%	363.93%
		CV	65.01%	66.48%	65.00%	75.42%	71.75%	75.49%
		K-S	P < 0.05	P < 0.05	P < 0.05	P < 0.05	P < 0.05	P < 0.05
	3	RMSE	473.63	519.54	490.53	591.00	531.42	645.82
		MAPE	154.23%	401.30%	307.02%	151.84%	409.85%	346.24%
		CV	61.33%	67.27%	63.52%	76.53%	68.81%	83.27%
		K-S	P < 0.05	P < 0.05	P < 0.05	P < 0.05	P < 0.05	P < 0.05
	4	RMSE	463.36	568.52	478.56	596.76	543.27	638.60
		MAPE	148.06%	1096.75%	312.70%	244.69%	658.68%	428.17%
		CV	60.00%	73.62%	61.97%	77.27%	70.35%	82.34%
		K-S	P < 0.05	P < 0.05	P < 0.05	P < 0.05	P < 0.05	P < 0.05
Meter-and-survey-based	5	RMSE	464.83	559.40	480.99	607.60	529.20	606.03
		MAPE	141.18%	1091.10%	319.59%	246.77%	648.87%	482.99%
		CV	60.19%	72.43%	62.28%	78.68%	68.52%	78.14%
		K-S	<u>P > 0.05</u>	P < 0.05	P < 0.05	P < 0.05	P < 0.05	P < 0.05
	6	RMSE	463.71	552.28	480.66	612.64	535.06	649.09
		MAPE	136.83%	971.83%	295.40%	248.17%	610.60%	435.52%
		CV	60.04%	71.51%	62.24%	79.33%	69.28%	83.70%
		K-S	P < 0.05	P < 0.05	P < 0.05	P < 0.05	P < 0.05	P < 0.05
Survey-based	7	RMSE	567.00	616.20	573.48	707.76	607.38	678.23
		MAPE	784.87%	983.66%	841.59%	654.82%	724.86%	834.78%
		CV	73.42%	79.79%	74.26%	91.65%	78.65%	87.45%
		K-S	P < 0.05	P < 0.05	P < 0.05	P < 0.05	P < 0.05	P < 0.05
	8	RMSE	554.31	611.49	549.68	687.56	600.08	654.68
		MAPE	773.16%	925.88%	793.87%	548.82%	722.38%	710.25%
		CV	71.78%	79.18%	71.18%	89.03%	77.70%	84.42%
		K-S	P < 0.05	P < 0.05	P < 0.05	P < 0.05	<u>P > 0.05</u>	P < 0.05

Figure 5.6 shows the RMSE of predicted results of scenarios in Group 1 and illustrates the impact of change in feature settings on the RMSE per algorithm. In the x-axis of

Figure 5.6, the note below the scenario id represents features in that scenario or the feature difference compared with the scenario on the left of it. Figure 5.6 shows that weather features in Scenario 2 have little impact on the RMSE except for deteriorating the performance of LSTM. Energy tariff, household and individual attributes in Scenarios 3 and 4 can improve the performance of ANN and LightGBM but adversely impact other algorithms. In the meter-and-survey-based scenarios, appliance usage in Scenario 5 improves the performance of LSTM, RF and KNN but slightly deteriorates the performance of SVM. On the contrary, general activity features in Scenario 6 only improve the performance of RF. Due to optimal performances in their respective categories, Scenario 4 from meter-based models, Scenario 5 from meter-and-survey-based models and Scenario 7 as the survey-based model with no data leakage are selected for further testing in Groups 2 and 3. More discussion about meter-based, survey-based and meter-and-survey-based models is shown in Section 4.4.

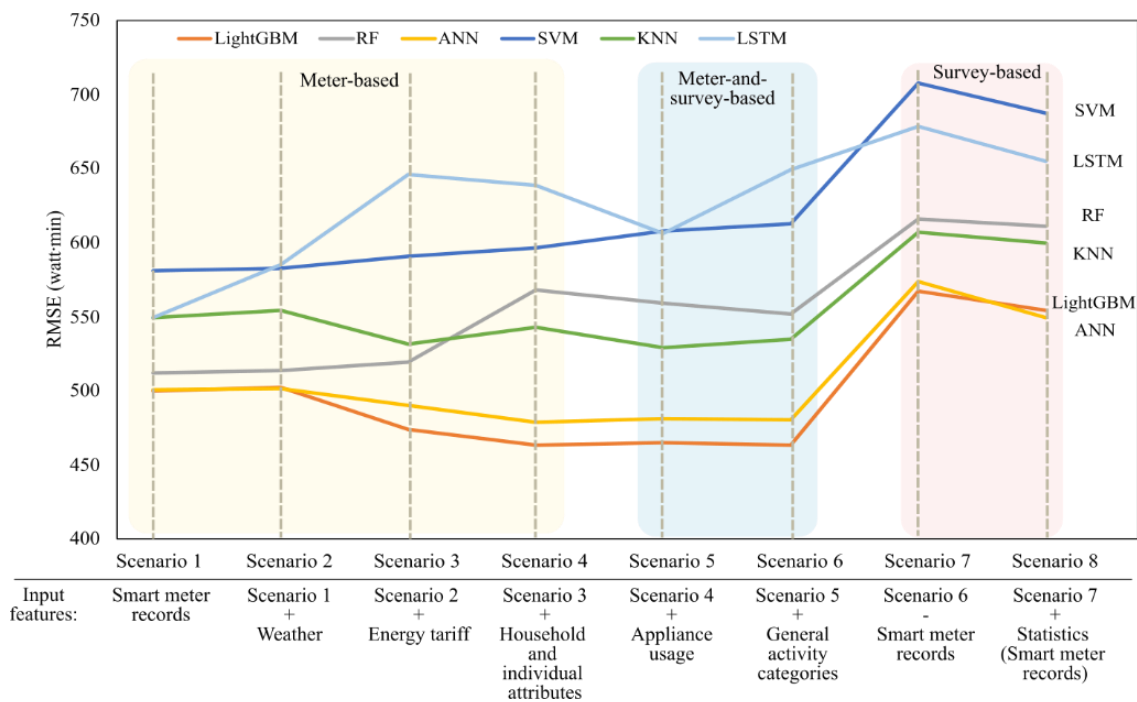


Figure 5.6 Results of input feature test Group 1

5.4.2 Group 2: Historical time window

Tables 5.3, 5.4 and 5.5 present the results of models in Group 2 with the input features of Scenarios 4, 5 and 7 in Group 1 respectively. For meter-based (see Table 5.3) and meter-and-survey-based (see Table 5.4) models, their best performances are both achieved by LightGBM models with features in the past 10 minutes (RMSE 458.09 and 458.92 respectively). For survey-based models (See Table 5.5), the best performance is

achieved by the LightGBM with features in the past 30 minutes (RMSE: 567.00). These results suggest the consistency of electricity consumption patterns in a short period is so strong that adding features in the earlier period may not necessarily improve the prediction accuracy. On the other hand, the impact of indoor activities on electricity consumption seems to last for at least 30 minutes, so the activity features in wider historical time windows are helpful in survey-based energy demand models.

Table 5.3 Results of the historical time window test (Group 2)
with meter-based Scenario 4

Scenario 4	Metrics	LightGBM	Random forest	ANN	SVM	KNN	LSTM
Past 10 minutes	RMSE	458.09	551.93	475.75	596.61	542.71	601.42
	MAPE	165.90%	1090.54%	300.56%	243.70%	831.18%	496.40%
	CV	59.42%	71.59%	61.71%	77.39%	70.39%	77.70%
Past 30 minutes	RMSE	463.36	568.52	478.56	596.76	543.27	638.60
	MAPE	148.06%	1096.75%	312.70%	244.69%	658.68%	428.17%
	CV	60.00%	73.62%	61.97%	77.27%	70.35%	82.34%
Past 60 minutes	RMSE	461.46	538.98	479.18	600.28	544.95	614.5
	MAPE	145.57%	584.75%	273.53%	227.18%	612.38%	391.18%
	CV	59.59%	69.60%	61.88%	77.51%	70.37%	79.01%
Past 120 minutes	RMSE	480.58	534.41	492.06	607.86	559.93	658.40
	MAPE	142.39%	464.40%	335.76%	230.89%	577.75%	388.31%
	CV	61.70%	68.61%	63.18%	78.05%	71.89%	84.18%

Table 5.4 Results of the historical time window test (Group 2)
with meter-and-survey-based Scenario 5

Scenario 5	Metrics	LightGBM	Random forest	ANN	SVM	KNN	LSTM
Past 10 minutes	RMSE	458.92	546.87	477.22	606.19	529.74	614.13
	MAPE	159.30%	1079.68%	276.18%	244.98%	819.93%	607.69%
	CV	59.53%	70.93%	61.90%	78.63%	68.71%	79.34%
Past 30 minutes	RMSE	461.83	559.40	480.99	607.60	529.20	606.03
	MAPE	141.18%	1091.10%	319.59%	246.77%	648.87 %	482.99%
	CV	60.19%	72.43%	62.28%	78.68%	68.52%	78.14%
Past 60 minutes	RMSE	461.75	532.44	482.12	614.53	533.08	607.72
	MAPE	140.53%	574.14%	266.57%	235.00%	599.51%	369.15%
	CV	59.62%	68.75%	62.26%	79.35%	68.84%	78.13%
Past 120 minutes	RMSE	481.80	525.50	498.47	626.49	564.89	609.20
	MAPE	136.71%	457.21%	336.94%	251.69%	557.47%	358.78%
	CV	61.86%	67.47%	64.00%	80.44%	72.53%	77.89%

Table 5.5 Results of the historical time window test (Group 2)

with survey-based Scenario 7

Scenario 7	Metrics	LightGBM	Random forest	ANN	SVM	KNN	LSTM
Past 10 minutes	RMSE	570.13	627.34	570.44	706.58	628.64	672.37
	MAPE	814.48%	1046.12%	854.61%	652.42%	803.02%	732.83%
	CV	73.95%	81.37%	73.99%	91.65%	81.54%	86.86%
Past 30 minutes	RMSE	567.00	616.20	573.48	707.76	607.38	678.23
	MAPE	784.87%	983.66%	841.59%	654.82%	724.86%	834.78%
	CV	73.42%	79.79%	74.26%	91.65%	78.65%	87.45%
Past 60 minutes	RMSE	578.00	612.74	573.76	720.54	610.72	705.95
	MAPE	792.54%	1080.46%	833.37%	667.93%	648.13%	781.49%
	CV	74.64%	79.12%	74.09%	93.04%	78.86%	90.76%
Past 120 minutes	RMSE	600.14	661.93	588.12	741.15	645.63	750.43
	MAPE	852.62%	979.01	809.14%	691.73%	712.88%	1278.74%
	CV	77.05%	84.99%	75.51%	95.16%	82.89%	95.95%

These impacts are shown in Figures 5.7, 5.8 and 5.9 as the RMSE (y-axis) of most algorithms rises with the increment of the width of historical windows (x-axis). Therefore, three types of models are selected for the test of different train-test splits in Group 3. They are Scenario 4 and Scenario 5 in Group 1 with features in the past 10 minutes, along with Scenario 7 in Group 1 with features in the past 30 minutes.

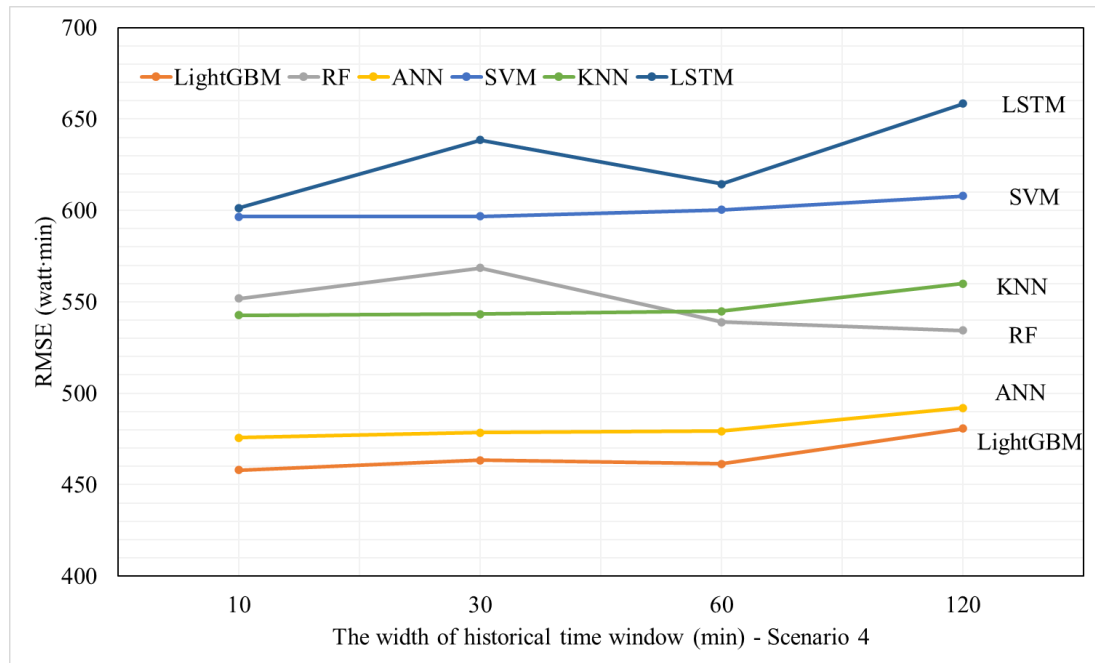


Figure 5.7 Results of the historical time window test (Group 2) with meter-based Scenario 4

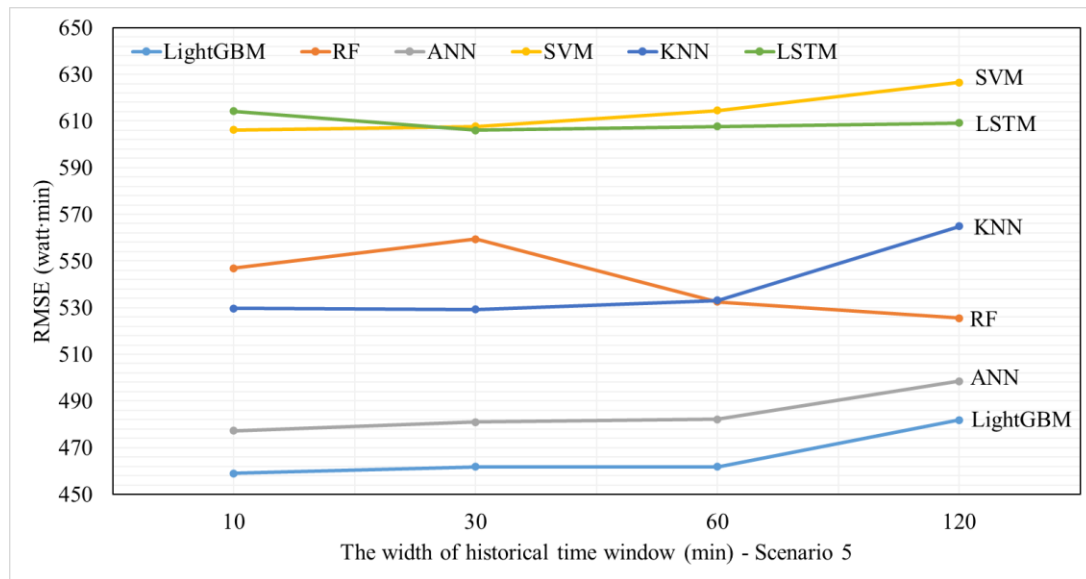


Figure 5.8 Results of the historical time window test (Group 2) with meter-and-survey-based Scenario 5

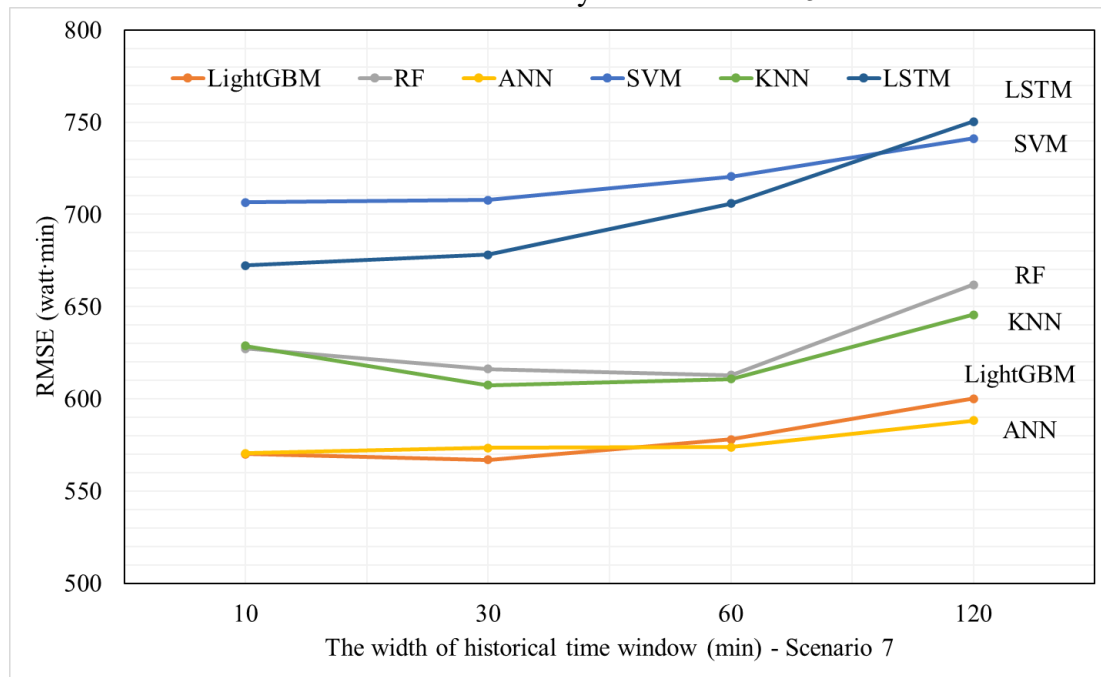


Figure 5.9 Results of the historical time window test (Group 2) with survey-based Scenario 7

5.4.3 Group 3: Train-test splits

The performances of models in Group 3 are shown in Tables 5.6, 5.7 and 5.8. LightGBM achieves the best performance when the dataset is split within households (“within data source”) in meter-based, meter-and-survey-based and survey-based models. When the train-test split changes from within households to across households (“between data sources”), the average RMSE increments are 13.42%, 11.14% and 21.65% for meter-based, meter-and-survey-based and survey-based models

respectively. In addition, ANN outperforms other algorithms in this context. The smallest RMSE increment is observed in meter-and-survey-based models, possibly due to the rich information derived from both meter and activity records. The comparison result of the two train-test splits is anticipated. When the dataset is split within households, available historical data in the same context provide adequate useful information about the load patterns. On the contrary, when the dataset is split across households, the source and target domain of ML algorithms are different, which leads to worse modelling performance. The prediction with different sources and target domains involves another branch of the ML research field: transfer learning (Pan & Yang, 2010) which is beyond the scope of this study.

Table 5.6 Results of the train-test split test (Group 3)
with Scenario 4, past 10 minutes

Metrics	LightGBM	Random forest	ANN	SVM	KNN	LSTM
Split within households						
RMSE	458.09	551.93	475.75	596.61	542.71	601.42
MAPE	165.90%	1090.54%	300.56%	243.70%	831.18%	496.40%
CV	59.42%	71.59%	61.71%	77.39%	70.39%	77.70%
Split across households						
RMSE	564.32	589.95	517.23	627.58	612.62	743.55
MAPE	67.04%	460.41%	187.75%	345.49%	385.05%	420.29%
CV	84.25%	91.90%	79.22%	93.25%	94.32%	117.42%
Compared to “Split within households”						
RMSE increase	23.19%	6.89%	8.72%	5.19%	12.88%	23.63%
Average Increase	13.42%					

Table 5.7 Results of the train-test split test (Group 3)
with Scenario 5, past 10 minutes

Metrics	LightGBM	Random forest	ANN	SVM	KNN	LSTM
Split within households						
RMSE	458.92	546.87	477.22	606.19	529.74	614.13
MAPE	159.30%	1079.68%	276.18%	244.98%	819.93%	607.69%
CV	59.53%	70.93%	61.90%	78.63%	68.71%	79.34%
Split across households						
RMSE	563.45	595.80	518.26	624.34	609.98	665.53

MAPE	79.58%	457.08%	214.86%	337.92%	406.53%	401.80%
CV	84.12%	93.02%	79.45%	92.76%	93.93%	102.30%
Compared to “Split within households”						
RMSE increase	22.78%	8.95%	8.60%	2.99%	15.15%	8.37%
Average Increase	11.14%					

Table 5.8 Results of the train-test split test (Group 3)
with Scenario 7, past 30 minutes

Metrics	LightGBM	Random forest	ANN	SVM	KNN	LSTM
Split within households						
RMSE	567.00	616.20	573.48	707.76	607.38	678.23
MAPE	784.87%	983.66%	841.59%	654.82%	724.86%	834.78%
CV	73.42%	79.79%	74.26%	91.65%	78.65%	87.45%
Split across households						
RMSE	735.41	800.29	715.35	712.61	788.87	780.14
MAPE	617.91%	687.50%	583.80%	546.42%	620.71%	478.82%
CV	110.28%	123.17%	110.58%	106.68%	120.97%	120.94%
Compared to “Split within households”						
RMSE increase	29.70%	29.88%	24.74%	0.69%	29.88%	15.03%
Average Increase	21.65%					

In all three groups of tests, the best performances are achieved by LightGBM with train-test split “within data source” across three model settings scenarios. These three model setting scenarios include meter-based Scenario 4 with features in the past 10 minutes, meter-and-survey-based Scenario 5 with features in the past 10 minutes and survey-based Scenario 7 with features in the past 30 minutes. Then, the comparisons between recorded and predicted loads within test datasets across these three scenarios are shown in Figure 5.10. These records are at 1-minute intervals from different households during different times so the ticks in the x-axis are omitted. This figure shows that the developed models predict the lower records more accurately than the sudden peak records. Model performance and predicted errors are discussed in the next sections.

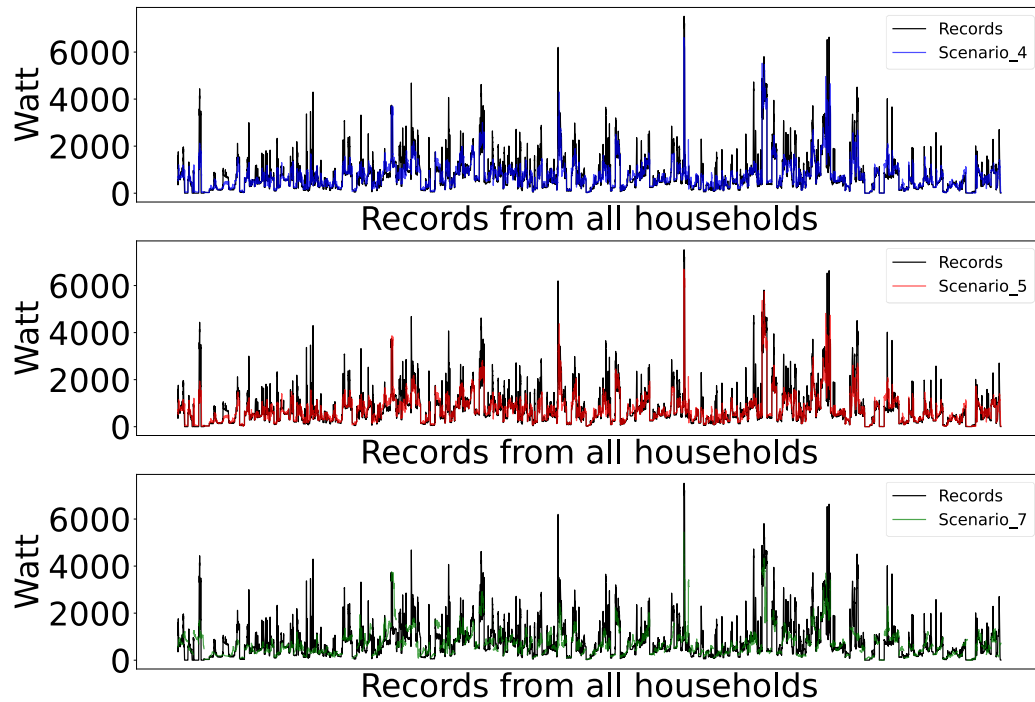


Figure 5.10 Prediction results (LightGBM in Group 3)

5.5 Discussion

5.5.1 The comparison between three types of models

Compared to the survey-based load profile generation method with conversion factors in Section 4.4.2, several sources of errors, such as the unknown “always-on” loads, absent end time of activities and the energy-related heterogeneity of households, are partly solved by ML algorithms in this chapter. Nevertheless, meter-based models and meter-and-survey-based models achieve better performance than survey-based models. The reasons for the underperformance of survey-based models are summarised.

- (1) The interval of 1 minute. The fine granularity of data strengthens the consistency between adjacent energy consumption patterns and probably magnifies the mismatch between activity records and energy consumption records.
- (2) Misrecorded activities. It is nearly impossible for the participants to manually record their activities at the exact time. One example is shown in Figure 4.13 in Section 4.4.
- (3) While ML algorithms can counteract some artefacts within the dataset, their passive impact on model performance persists. For example, the novel feature “Timecredit” is designed to mitigate the absence of the activity end times.

Table 5.2 shows that meter-based models and meter-and-survey-based models generally result in about 18% smaller errors (i.e., RMSE of LightGBM) than survey-based models. To better understand the model performance in different household contexts, and to discern the benefit of combining both meter-based and survey-based features, the prediction results in Group 1 were analysed per household. An intuitive assumption is that survey-based models might outperform meter-based models in predicting sudden load variation due to indoor activities. This sudden load change may disturb the consistency of electricity consumption patterns, consequently diminishing the effectiveness of meter-based models. Therefore, to represent the extent of sudden load variation of each household, the average of the standard deviation (std) of energy consumption records over every 120 minutes was calculated as the “average std”. Each spot in Figure 5.11 represents an algorithm’s prediction result of a household in one scenario in Group 1. The y-axis is RMSE and the x-axis is the calculated “average std”. Three best-fit linear trendlines were drawn based on all results of meter-based (Scenario 1 to 4), meter-and-survey-based (Scenario 5 to 6) and survey-based (Scenario 7 to 8) scenarios respectively. This figure shows that the larger “average std”, representing more sudden load variation, results in deteriorated prediction performance. The trendline of meter-and-survey-based scenarios (red) shows a less steep slope compared to those of the meter-based scenarios (blue) and survey-based scenarios (green). Therefore, combining both meter-based and survey-based features can robust the energy demand modelling performance against sudden load variation “average std”.

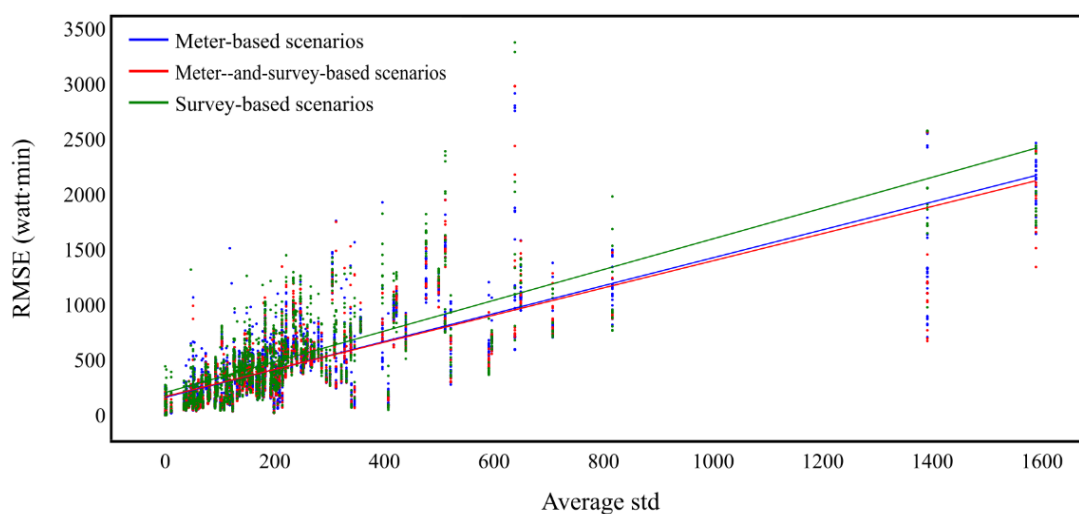


Figure 5.11 Per household analysis of test results in Group 1

The results in Tables 5.2, 5.4 and 5.7 show that the RMSE of meter-and-survey-based models, after combining meter-related and survey-related features, is still large. The main source of the remaining errors could be the fine granularity of the dataset and the accompanying sudden load variations. Electricity records at the minute level can capture more variations compared to hourly and half-hourly records. Meanwhile, Figure 5.10 shows the failure of models to predict these sudden peak loads and Figure 5.11 illustrates the positive correlation between RMSE and sudden load variation “average std”. Therefore, one direction for future work to improve the model performance can be training models separately for periods with and without sudden load variations as well as designing models to detect the sudden variation.

5.5.2 ML model performance

The test results and Figures 5.6 to 5.9 show that LightGBM and ANN outperform other algorithms in this multi-household dataset. Particularly, Tables 5.6, 5.7 and 5.8 show that LightGBM performs better when the train-test split is within households while ANN performs better when the train-test split is across households. Following the same analysis per household in the last section, each spot in Figure 5.12 represents an algorithm’s prediction result of a household in one scenario in Groups 1 and 2. Similarly, the y-axis is RMSE and the x-axis is “average std”. The best fit linear trendlines of algorithms also indicate that LightGBM and ANN are robust to the sudden load variation. On the other hand, LSTM and SVM do not perform well in the METER dataset, which is not consistent with previous research (Jeon & Kim, 2021; Bui et al., 2021; Edwards, New & Parker, 2012; Shabbir et al., 2019).

The different performances of algorithms may be explained by their particular application contexts and the characteristics of the dataset. The METER dataset contains short monitoring periods of multiple households. Various data sources in the dataset are not suitable for LSTM which is well-suited for long-term time series data from a single source. The basic idea behind SVM is to use kernel functions to transform data and find hyperplanes to separate data. However, multiple data sources in the METER dataset increase the difficulty to find proper kernel functions and hyperplanes. KNN and RF are famous for their easy deployment rather than their ability to address complex relationships. KNN takes advantage of its simple structure and the similarity

between the prediction target and the observation in the short past. RF is the ensemble model employing a bagging technique and multiple simple decision trees.

On the contrary, ANN is probably one of the most fundamental ML models that can contain multiple layers of various numbers of neurons. The complex connections between neurons make ANN more robust to the noise and capable of studying nonlinear relationships. Therefore, ANN may be more suitable for the METER dataset which has multiple data sources. LightGBM is a free and open-source distributed gradient boosting framework for machine learning originally developed by Microsoft. It is not a basic model like other ML algorithms tested in this study but a well-tuned and improved decision-tree-based model. LightGBM uses plenty of techniques to speed up the training and optimise the accuracy of results. More details can be found in the official document². Therefore, LightGBM outperforms other basic ML algorithms in this chapter.

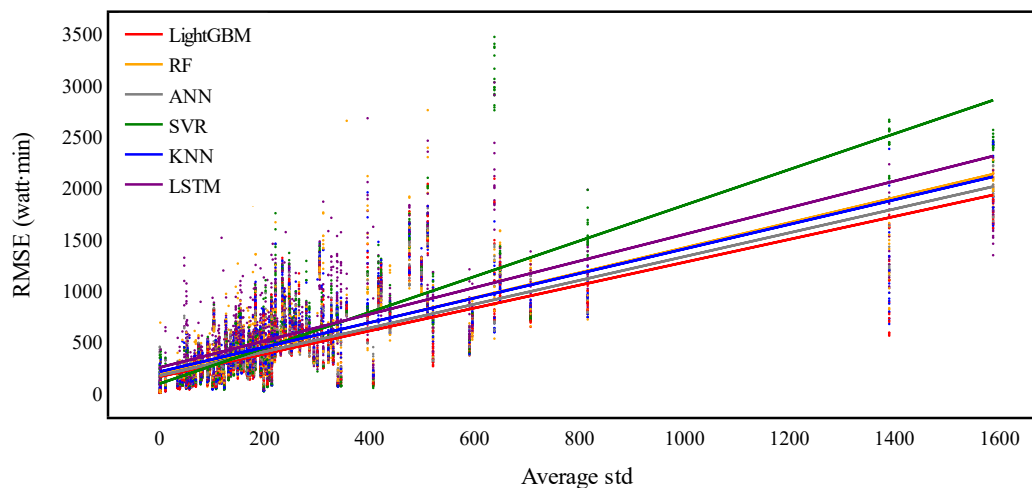


Figure 5.12 Per household analysis of algorithm performance

5.5.3 Limitations

This section summarises three main limitations of this chapter. First, the METER dataset lacks several important features and the sample size is small. The end time of activities and the power rate of appliances were not recorded, which deteriorates the performance of survey-based models. What is more, only 30 hours of novel simultaneous records of activities and energy consumption were recorded per household. These short periods weaken the models' ability to learn the trends and daily cycles of time-series electricity consumption. Despite the short period, the data

² <https://lightgbm.readthedocs.io/en/latest/Features.html>

collection of different households covers all months and seasons, represented by the calendar features such as the time of day, the day of week, month and seasons. The integration of calendar features and the potential mixed use of gas and electricity for heating in the participating households may make the contribution of weather features to electricity consumption prediction insignificant.

Second, this chapter designs a novel survey-related feature “TimeCredit” (see Section 5.2) to overcome the shortcomings of the missing activity end times and the sparsity of activity records in the METER dataset. This feature also attempts to capture the temporal impact of indoor activities on energy consumption and represent the overlap and interaction of activities. However, the assumption that ML methods can learn the boundary of activity impact and the interaction of activities based on this feature needs to be validated with more datasets.

Third, this chapter tests the performance of six popular ML algorithms. The grid search method was used to tune hyperparameters, such as the number of considered neighbours in KNN, the number of neural units in the neural network and regularization parameters in ML algorithms. Despite the hyperparameter optimisation, this tuning process in ML presents complexities, especially when dealing with a unique and novel dataset such as the METER dataset. Therefore, these results do not guarantee the same level of performance in other contexts. Testing different algorithms for different datasets and different contexts is essential (Amasyali & El-Gohary, 2021).

5.6 Summary

This chapter designs three groups of scenarios to test the performance of ML-based energy demand models. The first group of scenarios analyses the contribution of various demand influential features one by one and compares the prediction performance of meter-based, meter-and-survey-based and survey-based models. The second group of scenarios explores the impact of four widths of historical time windows of features. The third group of scenarios tests the energy demand models in two application contexts represented by different train-test split methods. Six popular ML algorithms are compared in all three test groups in a multi-household context built on the METER dataset. This dataset contains simultaneous meter and activity records, weather, energy tariff, household and individual attributes, appliance usage and general activity categories.

The novel conclusions of this chapter are summarised below:

- (1) Integrating appliance usage and general activity features into ML-based energy demand models can improve the prediction accuracy. The contributions of other factors, such as energy tariffs (Dai & Zhao, 2020) as well as household and individual attributes (Schirmer, Geiger & Mporas, 2021), have also been identified in this chapter and literature.
- (2) In the METER dataset, survey-based models are outperformed by meter-and-survey-based and meter-based models due to the fine granularity and misrecorded activities. Combining both meter-based and survey-based features can make the performance of the energy demand models robust against sudden load variation.
- (3) Meter-based and meter-and-survey-based models with features in a short preceding period of 10 minutes can achieve good performance. In contrast, survey-based models require features over earlier and longer periods, such as the past 30 minutes.
- (4) The performance of all models deteriorates when the train-test split switches from within households to across households, while the performance of meter-and-survey-based models is less affected than that of other models. This suggests that survey data assists in generalising the energy patterns learnt from the meter data.
- (5) Generally, LightGBM and ANN outperform other ML algorithms. LSTM and SVM may not be suitable in this multi-household short monitoring context. Particularly, LightGBM demonstrates superiority when the train-test split is within households, while ANN achieves better results when the train-test split is across households. In addition, the ability of ML-based models to offset the artefacts within the METER dataset needs to be validated.

In summary, there are three contexts where it is worth using electricity demand data with rich information about households and their activities in demand modelling: (a) The output of energy demand modelling is utilised for DSM associated with indoor activities; (b) Sudden load variations occur in the load profiles; (c) Energy demand models are used for targets with less historical data or targets that are different from the training data source. In these contexts, rich information about households and their

activities can help establish the relationship between indoor activities and energy demand, robust the model performance and generalise the energy patterns.

This chapter contributes to the knowledge of modelling energy demand in fine granularity using ML algorithms with various influential factors, different widths of historical time windows and disparate application contexts. These influential factors and model details are rarely studied in the literature. In addition, this chapter incorporates the overlap and interactions of activities using a designed feature “TimeCredit”. Future work could be validating these ML models in a larger dataset with simultaneous activity and meter records. What is more, models can be specifically trained to detect and predict sudden load variations to improve accuracy. Another direction is applying these ML models in DSM projects to achieve an accurate evaluation and efficient design. Consequently, the next chapter integrates the energy demand modelling framework and EV charging load generation model in Chapter 4, as well as the survey-based indoor load generation model in this chapter into DSM projects.

Chapter 6

DEMAND-SIDE MANAGEMENT ANALYSIS BASED ON COORDINATED LOAD PROFILES AND ACTIVITY INTERACTIONS

6.1 Overview

This chapter is contained in a peer-reviewed conference paper: Wang, H., Guo, F. & Sivakumar, A. (2023) Exaggerated potential for improvement in demand-side management with EV? Testing with observed and simulated consumer activities. Transportation Research Board Annual Meeting 2023.

Two previous Chapters 4 and 5 have developed a framework and tested several models to generate coordinated electric vehicle (EV) charging loads and household indoor loads based on cohesive activity profiles. This chapter develops a hybrid demand-side management (DSM) framework that incorporates the energy demand modelling framework in Chapter 4, the best-performing model in Chapter 5 and an evolutionary multi-objective optimisation algorithm NSGA-II. The objective is to integrate the connection between travel patterns and indoor activities, as well as multiple factors that influence energy demand into DSM. Furthermore, this DSM framework is tested with observed and simulated activity profiles to evaluate potential biases in the assessment of DSM. Sensitivity analysis is also conducted to study the impacts of the activity start times range and the distribution of off-peak hours in electricity tariffs.

DSM is the energy management technique that is used to modify the load pattern of the consumer (Kanakadhurga & Prabakaran, 2022). Although residential DSM has attracted extensive research attention, its real-world application is limited due to challenges in participant recruitment, concerns about participant satisfaction and the high requirement for communication systems. In addition, EVs have become an important element in DSM due to their increasing charging demand and correspondingly huge impact on the electricity network. However, observed real-world EV charging data are rare in the residential sector because of the current low penetration rate of EVs and privacy concerns in data sharing. Consequently, the potential for

improvement in DSM with EVs is usually evaluated in simulated contexts where bias may occur due to the simplification of consumer activities and EV usage.

Section 2.3 presents a detailed review of the load profile generation models for indoor household loads and EV charging loads, as well as the load profile reshaping mechanism in DSM. This review suggests that the potential for improvement in DSM may be exaggerated due to three reasons (a) the assumptions of normally distributed travel patterns; (b) the disconnect between indoor activity and travel patterns and (c) the simple straightforward relationship between indoor activities and electricity consumption, such as constant activity-to-power conversion factors. Accordingly, this chapter explores these three reasons and the potential for improvement in DSM based on observed and simulated activity profiles in the residential sector. The energy demand modelling framework designed in Chapter 4 and the preferred ML-based load profile generation models with multiple influential factors in Chapter 5 are also integrated. The specific objectives are three-fold:

- (1) Test the potential for improvement of DSM with three types of activity profiles to explore potential biases. The first type of activity profile consists of observed cohesive activity records that include both indoor activities and travel patterns from the same consumer. The second and third types of activity profiles consist of simulated interdependent indoor activities, coupled with normally distributed and survey-sampled car travel patterns respectively.
- (2) Design a hybrid multi-objective optimisation framework that incorporates the preferred ML-based indoor load profile generation model from Chapter 5 to consider the impact of multiple factors that influence demand in DSM.
- (3) Conduct sensitivity analysis in terms of ranges of activity start times and the distributions of off-peak hours in electricity tariffs to guide the design of DSM policies.

The METER dataset provides cohesive indoor activity profiles and travel pattern profiles. The term cohesive here refers to the fact that the indoor activity profiles and travel pattern profiles belong to the same consumer and are therefore consistent with each other. The London Travel Demand Survey (LTDS, 2018-2019) offers travel records that are utilised to simulate EV travel patterns and consequent electricity consumption. Additionally, car parking records from a residential estate in Singapore

are analysed to reveal car parking patterns and validate common assumptions in the literature. These datasets have been introduced in Chapter 3 and are further analysed in the next section. Consistent with the assumption made in Chapter 4, the observed car travel patterns, such as arrival and departure times, are assumed to remain unchanged when all cars in the study area are replaced by EVs (i.e., full electrification of the residential vehicle fleet).

The rest of this chapter is organized as follows. Section 6.2 analyses datasets and car parking patterns. Section 6.3 describes the model framework, problem formulation, simulation methods and optimisation strategies, followed by Section 6.4 which explains the experimental setup. Section 6.5 demonstrates results and sensitivity analysis. Section 6.6 discusses several rarely mentioned issues in DSM. Finally, Section 6.7 summarises this chapter.

6.2 Datasets

As discussed in Section 2.3.1, car travel patterns, such as arrival and departure times at home, may not follow the normal distribution in a small dataset. The following analysis of the METER dataset, LTDS and car parking records in Singapore supports this argument. This PhD research focuses on the UK context and models are built based on UK datasets. On the other hand, analysing travel patterns across different scales such as in a UK rural context (the METER dataset), a UK urban context (LTDS) and a Singapore urban context may reveal common patterns and inspire research in other contexts.

6.2.1 The METER dataset and LTDS

In the processed METER dataset in Section 5.2, 68 out of 160 households recorded 113 car trips. Figure 6.1 shows the distribution of the start and end times of car parking at home in the METER and LTDS datasets. The y-axis shows the count of car parking events that happened at the time slots in the x-axis. The large count of the end time in the METER dataset at 17:00 is due to the end of the monitoring period.

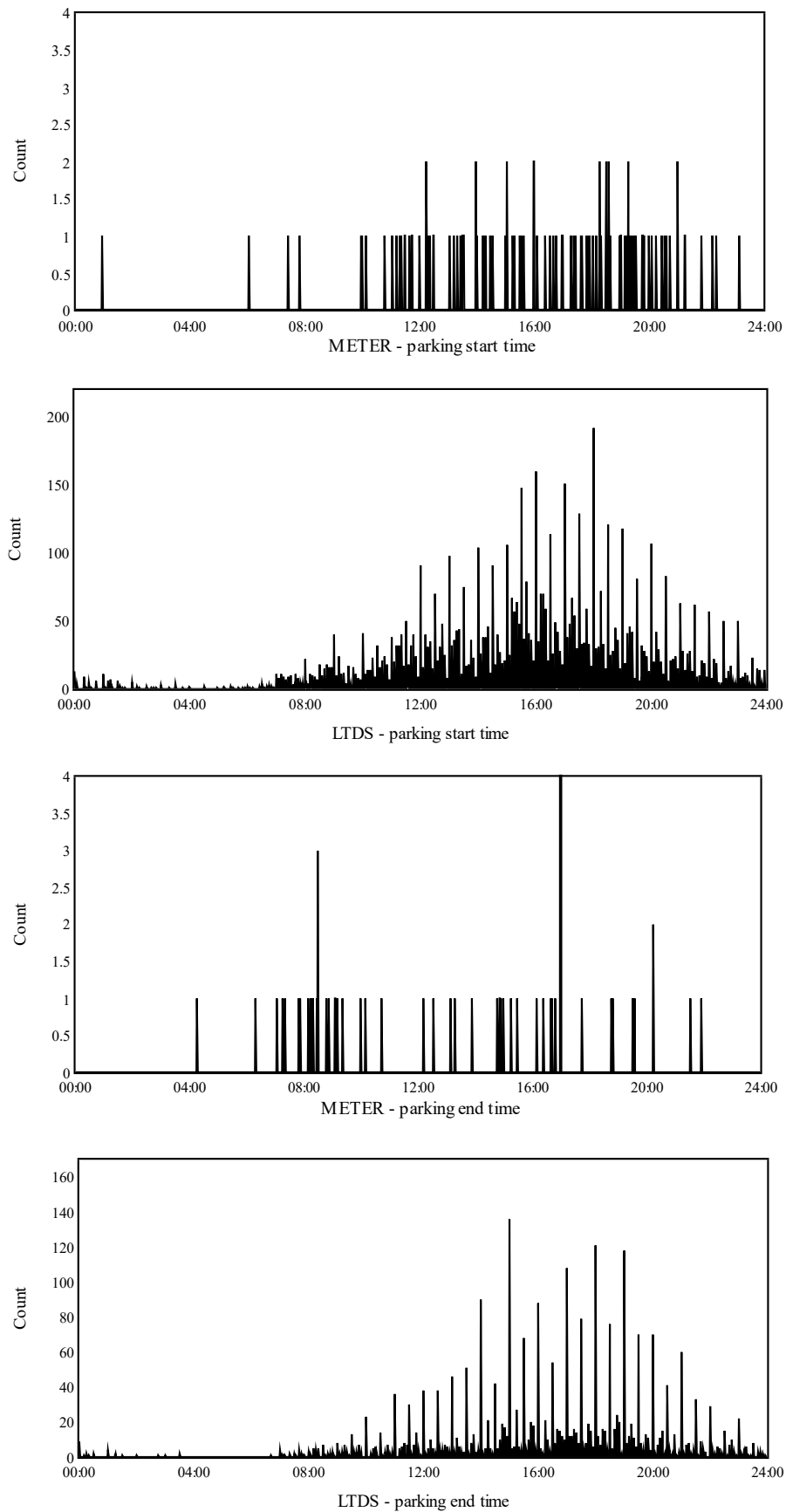


Figure 6.1 Histogram of the start and end times of car parking at home

Figure 6.2 shows the recorded daily car mileage in the LTDS. Figures 6.1 and 6.2 show that these travel patterns are not always normally distributed as assumed in the literature. For example, it is common to assume cars leave home with an average departure time of 08:00 with a variance of 30 minutes (Nan, Zhou & Li, 2018; Durillon et al., 2020). In addition, a large number of short car trips exist in these two datasets. Therefore, EV travel patterns simulated based on normal distributions may not represent reality, especially in datasets of similar size.

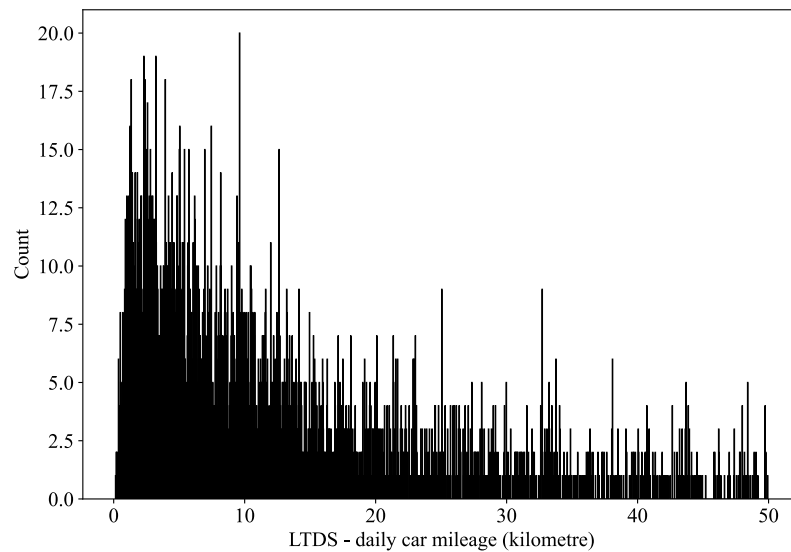
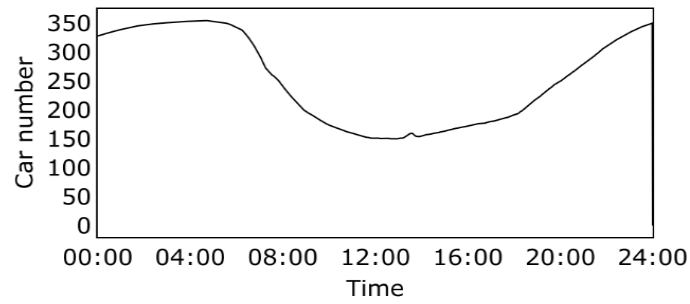


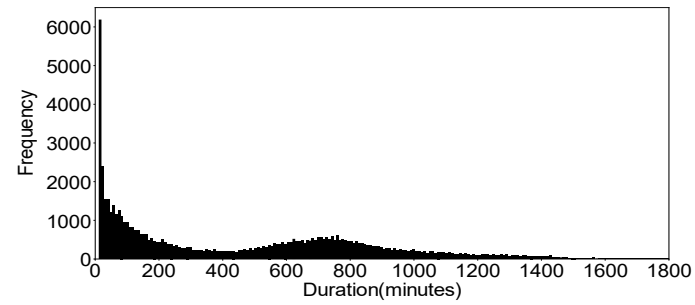
Figure 6.2 Histogram of daily car mileage

6.2.2 Car parking data from Singapore

The car parking records in an estate, including 7 residential blocks and a multi-story car park, in Singapore (see Section 3.2.4) are analysed. This Singapore dataset was first processed to remove duplicate records. In addition, parking events with durations of less than 10 minutes were removed since it was assumed that they would not be connected to the grid due to the short length of stay; in fact, it is quite likely that many of these are taxis. After the data processing steps, 67310 records were left with 5281 unique identifiers for the in-vehicle unit (IU) over 81 days (Jun 28 2022–Oct 05 2022). The average number of parked cars in the estate at each time slot throughout the day and the distribution of parking durations are shown in Figure 6.3. The distribution of the start and end times of car parking events with durations of more than 10 minutes is shown in Figure 6.4 and Figure 6.5.

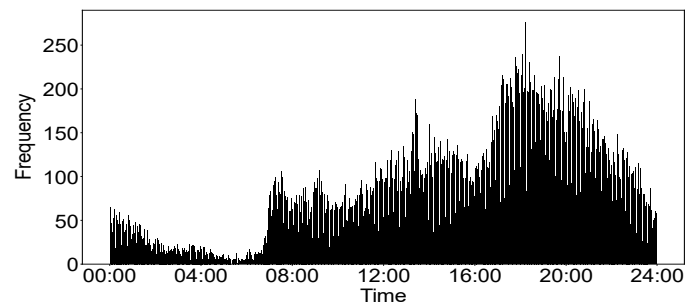


(a) The average number of parked cars during the day

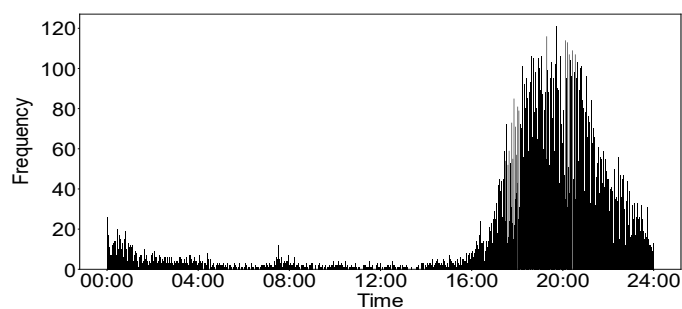


(b) The distribution of parking durations

Figure 6.3 Description of parking events

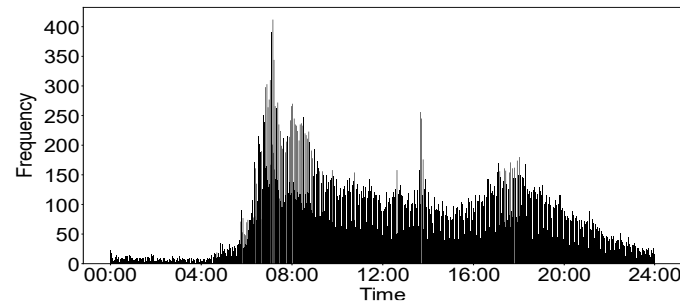


(a) Start times of parking events with durations of more than 10 minutes

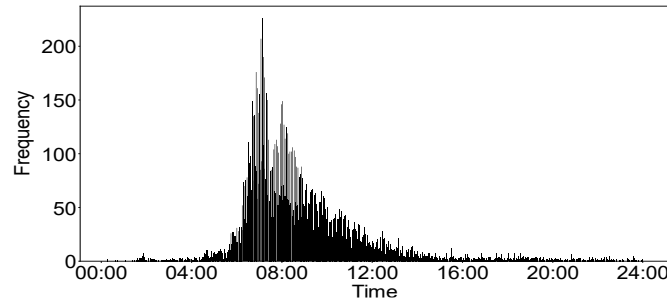


(b) Start times of parking events with durations between 600-900 minutes

Figure 6.4 Distribution of the start time



(a) End times of parking events with durations of more than 10 minutes



(b) End times of parking events with durations between 600-900 minutes

Figure 6.5 Distribution of the end time

These figures show that a large number of cars arrive in the community in the evening around 19:00 and may stay overnight, corresponding to the peak of 700 minutes in the distribution of parking duration in Figure 6.3 (b). At the same time, the number of cars arriving and departing in the daytime can not be neglected. Although cars arriving at the park before 4 pm or departing after 12 pm rarely stay for more than 600 minutes, the average number of parked cars in the estate throughout the day still exceeds 150 as shown in Figure 6.3 (a).

6.2.3 Discussion and summary

The average daily parking profile of the estate in Singapore includes 579 vehicles, identified by IU numbers, and 830 parking records. In other words, the average daily number of parking episodes is about 1.43 per vehicle in this Singapore residential estate. Correspondingly, the average daily number of home parking episodes is 1.44 per vehicle in the LTDS and 1.66 per vehicle in the METER dataset. Therefore, if a simple empirical probability distribution is used to generate parking records and each record is assigned the daily driving mileage, the generated charging demand will be about 43% to 66% larger than the actual demand.

The analysis of the METER dataset, LTDS and car parking records in Singapore shows that normally distributed arrival and departure times may not represent the reality of

travel patterns. What is more, the commonly used method to estimate EV charging demand based on empirical probability distributions may either exaggerate the number of vehicles or lose information on multiple parking events associated with the same vehicle. Therefore, EV charging demand derived from travel patterns based on normal distribution or empirical probability distribution may be inaccurate and cause bias in the design and assessment of DSM.

6.3 Methodology

6.3.1 Model framework

This chapter proposes a hybrid multi-objective DSM optimisation framework as shown in Figure 6.6.

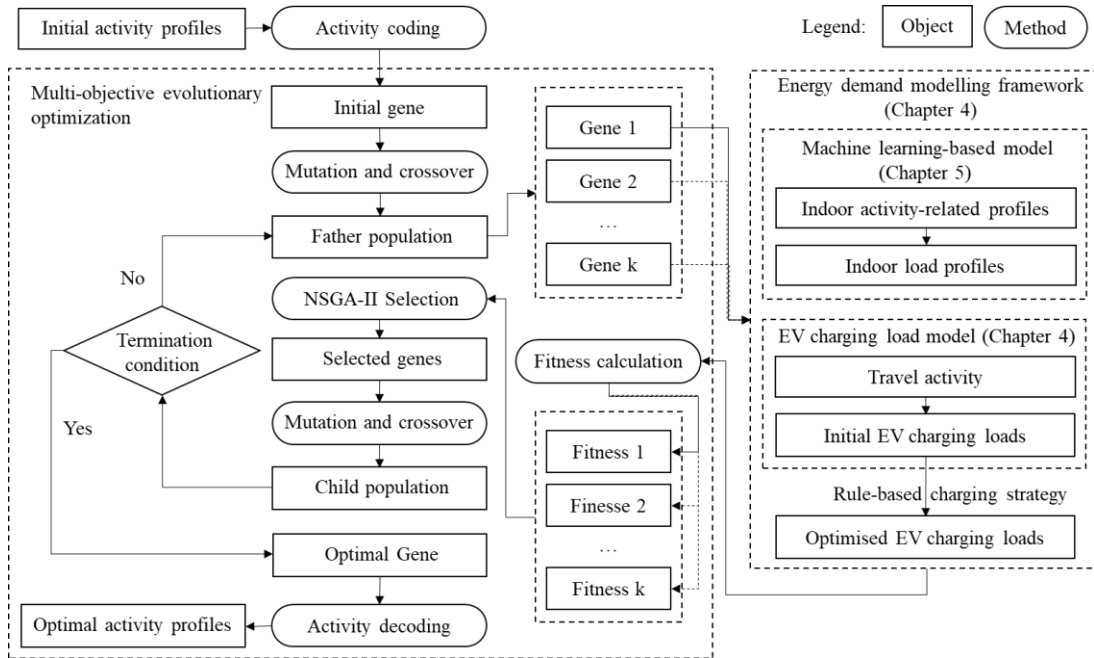


Figure 6.6 Model framework

This framework integrates the energy demand modelling framework in Chapter 4 and substitutes the indoor load generation model based on conversion factors with the ML-based model from Chapter 5. Such an integrated framework can maintain the connection between indoor activities and travel patterns in the initial profiles, as well as consider multiple factors that influence demand, such as simultaneous activities, electricity tariffs, timestamps and socio-demographics. In the optimisation process, a multiobjective evolutionary algorithm decides the start times of indoor activities and generates the optimal overall activity profiles, while rule-based charging strategies are designed for EVs. Components in the framework are explained in the next sections.

6.3.2 Problem formulation

This DSM framework sets two objectives to represent the interests of the grid and consumers respectively, i.e., minimising the Peak-to-Average Ratio (PAR) from the grid perspective and the monetary cost of buying electricity from the grid from the consumer perspective. Decision variables are the start time of flexible indoor activities and the charging status of EVs during the available charging periods. The model formulation is proposed below.

6.3.2.1 Objective functions

The first objective is PAR in Equation (6.1), which measures how flat the load profile is (de Souza Dutra & Alguacil, 2020). PAR is directly related to the operation of substations and electricity plants. Small PAR is likely to bring out economic benefits mainly for the grid (Li et al., 2017; Imran et al., 2020).

$$PAR = \frac{\max(\sum_{i=0}^n (L_{i,t}^{indoor} + L_{i,t}^{EV}))}{\frac{1}{T} (\sum_{t=1}^T \sum_{i=1}^n (L_{i,t}^{indoor} + L_{i,t}^{EV}))} \quad (6.1)$$

where $L_{i,t}^{indoor}$ is the indoor load of household i at time t , $L_{i,t}^{EV}$ is the charging load of EVs in the household i at time t , T is the number of time slots and n is the number of households.

The second objective, the monetary cost of electricity C , is shown in Equation (6.2).

$$C = \sum_{t=0}^T (P_t \times \sum_{i=1}^n (L_{i,t}^{indoor} + L_{i,t}^{EV})) \quad (6.2)$$

where P_t is the electricity price at the time t .

6.3.2.2 Indoor load profile model

In the indoor load profile model, the start time of flexible indoor activities can be rescheduled within the range as shown in Equation (6.3). A static occupancy schedule is assumed indicating the rescheduled activity start time should be within the home-stay duration as shown in Equation (6.4). The only decision variable for flexible indoor activities is the start time as the activity duration is indicated by the designed feature “TimeCredit” and the power rate at each time slot is determined by the ML-based load profile generation model.

$$\widehat{T}_{i,j} - \Delta t_{i,j} \leq T_{i,j} \leq \widehat{T}_{i,j} + \Delta t_{i,j} \quad (6.3)$$

$$\widehat{T_{i,j,s}} \leq T_{i,j} \leq \widehat{T_{i,j,e}} \quad (6.4)$$

where $T_{i,j}$ is the rescheduled start time of activity j in household i , $\widehat{T_{i,j}}$ is the original start time of activity j , $\Delta t_{i,j}$ is the allowed range of activity start times, $\widehat{T_{i,j,s}}$ and $\widehat{T_{i,j,e}}$ are the start and end times of the occupancy at home which cover the original activity j .

The preferred ML-based load profile generation model from Chapter 5, LightGBM, is adapted to simulate electricity consumption based on the weather, electricity tariffs, household and individual attributes, appliance usage, and general activity categories (Equation (6.5)). This ML-based model will be briefly reintroduced in the following Section 6.3.4.

$$L_{i,t}^{Indoor} = f_{LightGBM}(W(i,t), P(t), H(i), A(i,t), AC(i,t)) \quad (6.5)$$

Where $f_{LightGBM}$ is the ML-based indoor load generation model, $W(i,t)$ is the set of weather-related variables, $P(t)$ is the set of price-related variables, $H(i)$ is the socio-demographics of household i , $A(i,t)$ is the set of activity-related variables, $AC(i,t)$ is the set of variables for general activity categories.

This chapter considers the same types of flexible indoor activities and appliance usages as those recorded in the METER dataset and studied in Chapter 5, including washing machines, dishwashers, TV, information and communication technology (ICT), kettles, making breakfast, making lunch, making dinner, oven, hob, microwave, toaster and shower. The details of these features can be seen in Appendix 1.

6.3.2.3 Electric vehicle model

The EV charging load estimation model in Section 4.3.1 is adapted to simulate the initial uncontrolled charging profiles and State-of-Charge (SOC). The energy consumption of EVs is estimated based on driving duration, driving speed and energy efficiency. The average driving speeds of trips with different purposes are estimated based on the LTDS dataset.

EVs are supposed to be fully charged in the beginning and the valid household charging time of EVs is the period between the arrival and departure of EVs. The discharging of EVs (through vehicle-to-grid or vehicle-to-household technologies) is not considered in this model as this technology is not the focus of this chapter and will introduce extra

assumptions, such as charging sites outside of the home and different selling prices for discharged electricity.

The uncontrolled EV charging estimated in Section 4.3.1 provides the initial SOC at the start and end of trips which guarantee trip completion. These initial SOC then become the constraints for the optimised EV charging in this model to ensure the next trip is not affected by DSM. Unlike the model in Section 4.3.1, the charging rate in this study is constant but the charging status during the valid charging period can be controlled. In summary, the electric vehicle model is shown below (Equation (6.6)-(6.11)) :

$$E_m = D_m \times e \quad (6.6)$$

$$D_m = v_m \times T_m \quad (6.7)$$

$$S_{n,m-end}^{EV} = S_{n,m-start}^{EV} - E_m / E^{EV,max} \quad (6.8)$$

$$L_{n,t}^{EV} = CR^{EV} I_{n,t}^{EV} \quad (6.9)$$

$$S_{n,t}^{EV} = S_{n,t-1}^{EV} + L_{n,t}^{EV} / E^{EV,max}, \quad S_{n,t}^{EV} \leq 1 \quad t=0, 1, 2 \dots d \quad (6.10)$$

$$S_{n,T_d}^{EV} = \widehat{S_{n,T_d}^{EV}} \quad (6.11)$$

where E_m is the energy consumption (kWh) of the EV during trip m , D_m is the driving distance (km) of trip m , e is the energy efficiency (kWh/km) of the EV, v_m is the average driving speed (km/minute) of trips by purpose (based on trips in the LTDS that have the same purpose as the trip m), T_m is the driving duration (minutes) of the trip m , CR^{EV} is the constant charging rate of EVs at home, $I_{n,t}^{EV}$ is the binary variable showing the charging status of the n -th EV, $S_{n,t}^{EV}$ is the SOC of EV n at time t , $\widehat{S_{n,T_d}^{EV}}$ is the initial SOC when parking ends and the next trip starts, $E^{EV,max}$ is the battery capacity of EVs, and d is the end time of EV charging.

6.3.3 Multi-objective evolutionary optimisation

The integration of an ML-based model challenges the conventional deterministic optimisation algorithms such as mixed-integrated programming (MIP). Therefore, nondominated sorting genetic algorithm II (NSGA-II), a computationally fast and elitist multi-objective evolutionary algorithm, is used. NSGA-II is designed based on the

genetic algorithm and was widely used to solve the optimisation problem in DSM (Amasyali & El-Gohary, 2021; Yang et al., 2021).

Details of NSGA-II can be found in (Deb et al., 2002) and the implementation of NSGA-II in this chapter is briefly explained in the following steps.

- (1) Step 1: The initial activity profiles of a group of households are coded based on the decision variables, i.e., the start times of activities and the charging status of EVs. The result is referred to as the initial gene, which is one set of coded activity profiles;
- (2) Step 2: The initial gene is processed by mutation and crossover operators to generate multiple genes, forming the father population, i.e., multiple sets of coded activity profiles for households. The number of genes is known as population size k , as shown in Figure 6.6. During this process, several predetermined probabilities guide the mutation operators to randomly substitute the original activity start time with another feasible start time. Similarly, the crossover operators exchange the activity start times between households with the same socio-demographics but from different genes;
- (3) Step 3: The indoor load profiles are estimated for each gene in the father population by utilising the ML-based indoor load profile generation models in Chapter 5. Similarly, the EV charging load profiles for each gene are adapted following the rule-based charging strategies stated in Section 6.3.5;
- (4) Step 4: The fitness is calculated for each gene based on its load profiles and the two objectives in Section 6.3.2.1;
- (5) Step 5: The NSGA-II selection mechanism (Deb et al., 2002) is used to select a certain number of suitable genes from the father population considering both the best fitness and the diversity in genes. The selected genes go through Step 2 and then form the child population with the same size k ;
- (6) Step 6: Termination conditions are designed to determine whether to set the child population as the new father population and iterate Step 3 to Step 6 or to end the iteration. The termination conditions are usually the maximum iteration times and the reduced improvement of fitness over a certain number of iterations;
- (7) Step 7: When the iteration ends, the best genes are selected and decoded into

optimal activity profiles for households. For multi-objective problems, the result will be a Pareto-optimal set of activity profiles to preserve diversity.

6.3.4 Indoor load profile: ML-based load profile generation

In the literature on DSM, the prevalent indoor load generation method is to convert activity patterns to load based on constant activity-specific factors (Durillon et al., 2020; Anvari-Moghaddam et al., 2017; Kurniawan et al., 2020). Despite the wide application in solving prediction problems, ML-based models are rarely used in this domain partly due to the limited access to training data that contains simultaneous activity and meter records. In addition, most ML-based models will introduce the non-linear relationship between activity and loads into DSM, challenging the conventional deterministic optimisation methods. Chapter 5 on the other hand shows that to obtain accurate load profiles, the nonlinear relationship between indoor loads and many other influential factors, such as socio-demographics, electricity tariffs and simultaneous activities, need to be considered. Furthermore, six types of ML-based load profile generation methods have been tested and preferred methods are suggested in different scenarios. Meanwhile, the heuristic optimisation algorithm NSGA-II can address the non-linear relationship between activity and loads in the optimisation process. Therefore, LightGBM, the preferred ML algorithm indicated in Chapter 5, is utilised in this chapter to generate indoor load profiles.

Similar model settings are adapted from Chapter 5. For example, the input features include the same five feature groups except for the historical meter records, i.e., weather, electricity tariffs, household and individual attributes, appliance usage, and general activity categories. The width of the historical window of features is 30 minutes. The novel feature “TimeCredit”, which means the extent to which an activity is believed to happen or endure around a time slot based on the temporal distance to the recorded start/end time, is also utilised. This feature captures the lasting impact of indoor activities and offsets the drawbacks of both the missing end time and the sparsity of activity records. In addition, the “TimeCredit” of different indoor activities may overlap, which represents the presence of simultaneous activities and the interactions between them.

6.3.5 EV charging load profile: Rule-based charging strategies

Rule-based charging strategies, instead of NSGA-II, are designed for EVs for two

reasons: (a) The decision variable for EVs, charging status, can be directly transferred to the charging loads by multiplying the constant charging rate, while the start times of indoor activities need to be fed into an ML-based model; (b) The EV model has more constraints which will increase the complexity of operators in NSGA-II. During the valid EV charging period, time slots are picked according to the following strategies and the simultaneous EV charging status is set until the EV charging demand is met. Two EV charging strategies are designed for the two objectives, i.e., electricity cost and PAR.

- (1) “Cost first”: Time slots with lower electricity prices have higher priority for EV charging. Notably, within periods when the prices are the same, EV charging should avoid time slots with local peak load. For example, during the off-peak hours with the same low prices, the “PAR first” strategy below is applied.
- (2) “PAR first”: Time slots with lower indoor loads have higher priority for EV charging.

6.4 Experimental setup

Three types of activity profiles, five levels of the ranges of activity start times and two distributions of off-peak hours in electricity tariffs are tested in the proposed DSM framework. For the NSGA-II, the population size k is 32, crossover probability of 80% and mutation probability of 40% are referenced from the literature (Lu et al., 2015; Zuhaib, Hajdukiewicz & Goggins, 2019; Amasyali & El-Gohary, 2021). The activity profiles and sensitivity analysis setup are described below.

6.4.1 Initial activity profiles

Three types of initial daily activity profiles are tested:

- (1) Profile 1 “Survey”: Observed activity profiles in the METER dataset (113 EV trips consuming 356.65 kWh).
- (2) Profile 2 “Simulated_Normally”: Simulated indoor activity profiles with normally distributed EV usage (76 EV trips consuming 484.20 kWh).
- (3) Profile 3 “Simulated_Sampled”: Simulated indoor activity profiles with survey-sampled EV usage (230 EV trips consuming 433.03 kWh).

As discussed in the literature review, activity profiles are usually simulated based on

probability distributions, ignoring the difference between households. In alignment with this existing method, a time-inhomogeneous Markov Chain model was built to simulate activity profiles based on the transition probabilities extracted from the METER dataset. The flexible indoor activities considered and the flexible usage of appliances are categorised into three groups as shown below (Nazemi, Jafari & Zaidan, 2021; Goyal & Vadhera, 2021; Bissey, Jacques & Le Bunetel, 2017; Bilton et al., 2014):

- (1) High flexibility: washing machine, dishwasher
- (2) Medium flexibility: TV, ICT
- (3) Low flexibility: kettle, making breakfast, making lunch, making dinner, oven, hob, microwave, toaster, shower

Observed and simulated indoor activity profiles have similar frequencies of activities as the average absolute difference in the frequency is 11.56%. The same socio-demographics and weather profiles are inherited from the METER dataset for these households.

EVs are assigned to simulated households based on the vehicle penetration rate in the METER dataset. All EVs have the same parameters, i.e., usable battery capacity (40 kWh) and energy efficiency (0.149 kWh/km) based on the Tesla Model 3 which is the most common generic model of Ultra Low Emission Vehicles registered for the first time in the UK (Department for Transport, 2021). The maximum charging rate is the typical household charging rate of 3.7 Kw (Fischer et al., 2019; Sun, Neumann & Harrison, 2020). In the observed activity profile, the start and end times of trips, driving duration and driving purposes are extracted from the METER dataset. Normally distributed travel patterns are simulated based on a common setting where cars leave and arrive at home with the average departure and arrival times at 8:00 and 18:00 respectively, and both variances are 30 minutes (Nan, Zhou & Li, 2018; Durillon et al., 2020). Survey-sampled EV travel profiles extract individual daily car trips from the LTDS. The EV trip numbers and EV charging demand are not normalised for these three profiles. The reason is that there is very little knowledge of real EV trip numbers and charging demand in the literature to normalise simulated EV usage profiles. Therefore, to explore all the potential biases in applying simulated profiles in DSM, EV usage is not normalised in this chapter.

6.4.2 Sensitivity analysis setup

The sensitivity analysis includes five levels of ranges of activity start times and two distributions of off-peak hours in electricity tariffs, as shown in Table 6.1. Level 3 of the ranges was referenced from the literature (Nazemi, Jafari & Zaidan, 2021; Goyal & Vadhera, 2021; Bissey, Jacques & Le Bunetel, 2017; Bilton et al., 2014) and other levels are scaled-up and down arbitrarily relative to Level 3.

Two distributions of off-peak hours derived from real electricity tariffs in the UK, Economy 10 and Economy 7³, are tested by assigning each of them to all households to analyse their impact. In Project METER, there are 23 households with Economy 7 tariffs and 2 households with Economy 10 tariffs. The approximations of their recorded prices are utilised in this chapter, setting the off-peak price at 0.06 £/kWh and the peak price at 0.16 £/kWh. Notably, this set of peak and off-peak prices is used for both tariffs to exclude the impact of different price values across tariffs.

Table 6.1 Sensitivity analysis setup

Range of activity start times (minutes)					
$\Delta t_{i,j}$	Level 1	Level 2	Level 3	Level 4	Level 5
High	45	90	180	360	720
Medium	30	60	120	240	480
Low	5	10	20	40	80
Distribution of off-peak hours					
Tariffs	Economy 10		Economy 7		
Off-peak hours	(1) Midnight – 5 am (2) 1 pm – 4 pm (3) 8 pm – 10 pm		Midnight – 7 am		

In summary, three types of activity profiles, five levels of ranges of activity start times and two distributions of off-peak hours in electricity tariffs result in thirty test scenarios. For each scenario, five stages during the optimisation process are analysed to show the influence of scheduling EV charging and indoor activities respectively, as shown in Figure 6.7.

(1) Stage 1: Unoptimised indoor activity with uncontrolled EV charging.

(2) Stage 2: Unoptimised indoor activity with “Cost first” EV charging.

³ Economy 7 wikipedia: https://en.wikipedia.org/wiki/Economy_7; Economy 10 wikipedia: https://en.wikipedia.org/wiki/Economy_10

- (3) Stage 3: Unoptimised indoor activity with “PAR first” EV charging.
- (4) Stage 4: Optimised activity profiles with minimum cost.
- (5) Stage 5: Optimised activity profiles with minimum PAR.

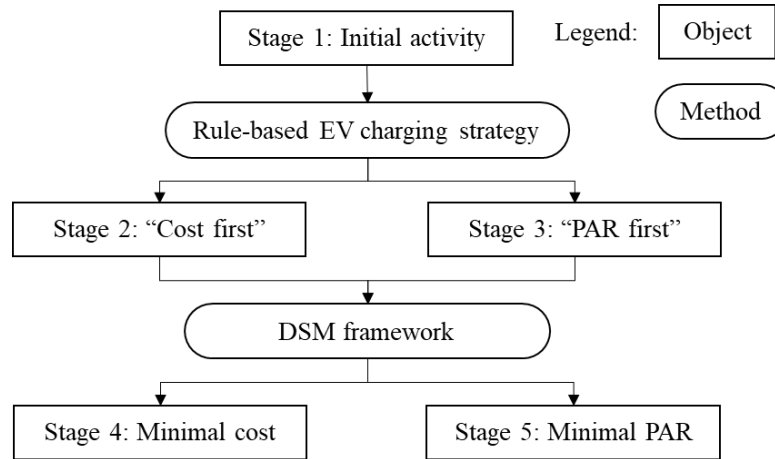


Figure 6.7 Stages of profiles

6.5 Results

6.5.1 Observed and simulated activity profiles

The optimisation results of three initial activity profiles with the Level 3 ranges of activity start times and the distribution of off-peak hours in the Economy 10 tariff are shown respectively in Tables 6.2, 6.3 and 6.4. This particular set of ranges is employed in the initial analysis of activity profiles due to their prevalent usage in the domain.

Table 6.2 Results of Profile 1 “Survey” with Economy 10

Profile 1	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
Indoor activity	Unoptimised	Unoptimised	Unoptimised	Optimised with minimum cost	Optimised with minimum PAR
EV charging	Uncontrolled	“Cost first”	“PAR first”		
Electricity cost (£)					
Value	304.00	290.82	306.00	289.29	305.64
Compared to Stage 1	-	-4.34%	+0.65%	-4.84%	+0.54%
PAR					
Value	1.78	1.61	1.50	1.62	1.46
Compared to Stage 1	-	-9.07%	-15.31%	-9.04%	-17.94%

The average absolute load difference percentage from Stage 1 (per minute)					
Total load	-	13.49%	10.13%	14.13%	10.65%
Indoor load	-	-	-	1.42%	1.10%
EV charging load	-	101.21%	76.06%	101.08%	75.80%

Table 6.3 Results of Profile 2 “Simulated_Normally” with Economy 10

Profile 2	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
Indoor activity	Unoptimised	Unoptimised	Unoptimised	Optimised with minimum cost	Optimised with minimum PAR
EV charging	Uncontrolled	“Cost first”	“PAR first”		
Electricity cost (£)					
Value	327.81	287.27	315.85	286.73	311.13
Compared to Stage 1	-	-12.37%	-3.65%	-12.53%	-5.09%
PAR					
Value	2.76	1.48	1.38	1.47	1.32
Compared to Stage 1	-	-46.62%	-49.93%	-46.69%	-52.33%
The average absolute load difference percentage from Stage 1 (per minute)					
Total load	-	33.23%	31.10%	33.74%	33.12%
Indoor load	-	-	-	0.97%	1.30%
EV charging load	-	189.35%	177.26%	188.52%	184.37%

Table 6.4 Results of profile 3 “Simulated_Sampled” with Economy 10

Profile 3	Stage 1	Stag 2	Stage 3	Stage 4	Stage 5
Indoor activity	Unoptimised	Unoptimised	Unoptimised	Optimised with minimum cost	Optimised with minimum PAR
EV charging	Uncontrolled	“Cost first”	“PAR first”		
Electricity cost (£)					
Value	314.50	291.43	312.62	290.79	312.85

Compared to Stage 1	-	-7.34%	-0.60%	-7.54%	-0.53%
PAR					
Value	1.72	1.69	1.41	1.70	1.36
Compared to Stage 1	-	-1.75%	-18.15%	-1.22%	-21.16%
The average absolute load difference percentage from Stage 1 (per minute)					
Total load	-	19.99%	13.54%	20.36%	13.81%
Indoor load	-	-	-	0.87%	1.00%
EV charging load	-	125.03%	84.67%	124.92%	85.44%

Tables 6.2, 6.3 and 6.4 show that simulated Profiles 2 (cost: -12.53%, PAR: -52.33%) and 3 (cost: -7.54%, PAR: -21.16%) achieve more reduction both in electricity cost and PAR compared with observed Profile 1 (cost: -4.84%, PAR: -17.94%). This indicates that the prevalent load profile simulation method (e.g., Profiles 2 and 3) based on separate indoor and travel activity profiles may exaggerate the potential for improvement in DSM by about 2 to 3 times.

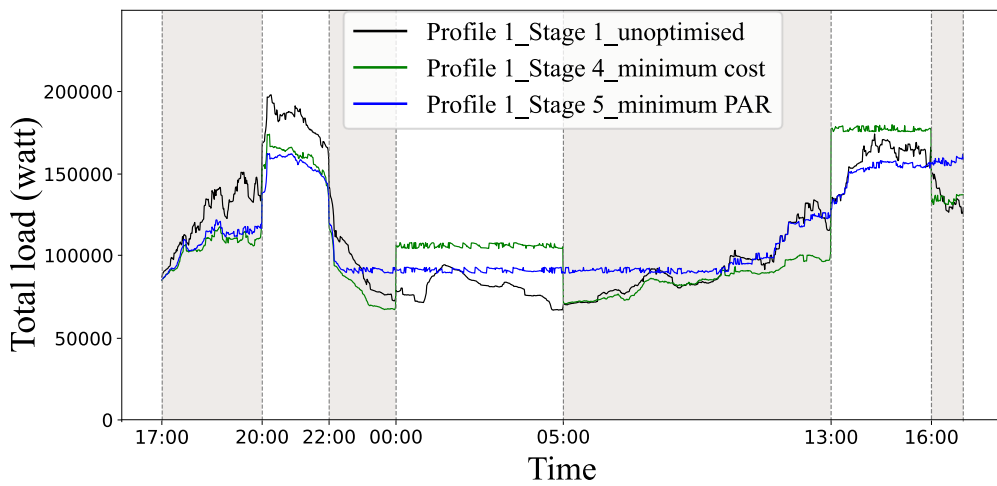
In addition, Stage 2 and Stage 4 achieve similar improvements. The EV charging loads are controlled to minimise cost in these two stages and the difference between them indicates whether the indoor activities are optimised. Similarly, Stage 3 and Stage 5 achieve similar improvements as EV charging loads are controlled to minimise PAR in these stages. The average absolute load difference per minute from Stage 1 in these three profiles also shows that the change in EV charging loads is larger than the change in indoor activity load. These results suggest that the control of EV charging contributes to more than 90% of improvements in cost and PAR reduction.

Figure 6.8 shows the results in Tables 6.2, 6.3 and 6.4, illustrating three sets of total load profiles both before and after DSM optimisation (e.g., Stages 1, 4 and 5), derived from three initial activity profiles respectively. The grey zones in the figure show the peak hours with higher electricity prices. These three sets of load profiles vary in terms of patterns and scales due to different schedules of indoor activities and EV travel activities. Normally distributed EV usage patterns in Profile 2 result in a peak EV charging load around the average arrival time in Stage 1, as represented by the black

line in Figure 6.8 (b). In addition, the average arrival time is close to the evening peak of indoor electricity consumption and then causes high PAR. However, due to the long parking period during the night, the peak EV charging load can be easily deferred to off-peak hours around midnight and achieve a large improvement. The load pattern of Profile 2 is vastly different from the other two profiles and may become an exception in later analysis.

On the other hand, survey-sampled EV usage in Profile 3 has less connection with indoor activities and thus results in a large number of small local peaks, as represented by the black line in Figure 6.8 I. In comparison, cohesive activity profiles in the observed Profile 1 may describe the schedule that involves people parking their EVs around the home for charging and conducting electricity-consuming indoor activities at the same time. This consistency of activities may generate relatively smoother total load profiles. What is more, since the survey-sampled trips are extracted from datasets in different contexts, the time of peak loads is different in Profile 3 from that in Profile 1.

Notably, in three sets of load profiles, the load curve is relatively smooth during the off-peak hours at night not only in the minimum PAR profiles but also in the minimum cost profile. The reason is that the majority of flexible EV charging loads occur at night, overlapping with the off-peak hours. During the off-peak hours with the same low prices, the “Cost first” charging strategy will allocate loads smartly to avoid local peak load since the cost does not increase.



(a) Profile 1

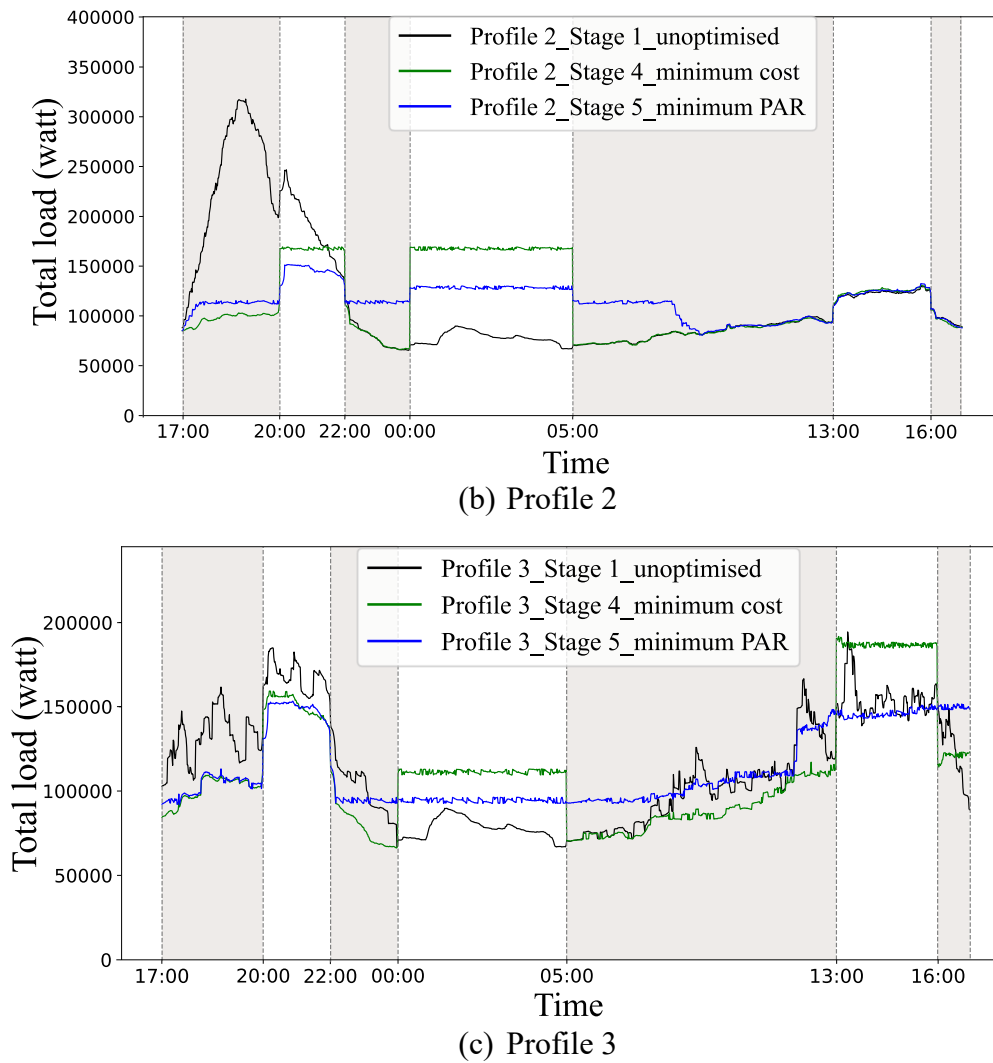


Figure 6.8 The total load in Stages 1, 4 and 5 with Economy 10

6.5.2 Sensitivity analysis

6.5.2.1 Activity start time range analysis

The optimisation results of three activity profiles with the five levels of ranges of activity start times and two distributions of off-peak hours in tariffs are shown in Figure 6.9. Solid and dashed patterns represent the results of the Economy 10 and Economy 7 tariffs respectively. The trend lines in Figure 6.9 show that a larger range of indoor activities allows a marginally larger percentage decrease in cost and PAR. This finding complies with the analysis in the previous section about Tables 6.2-6.4, which suggests that most improvement is driven by the rescheduling of EV charging and the change of indoor loads itself is small. This small change in indoor loads shows that the electricity consumed by flexible indoor activities may only take up a small proportion of total indoor loads. The underlying causes can be twofold. First, highly flexible and energy-

intensive indoor activities, such as using a washing machine or dishwasher, occur less frequently. Second, the start time range of frequently occurring indoor activities, such as using a kettle or cooking, is relatively narrow.

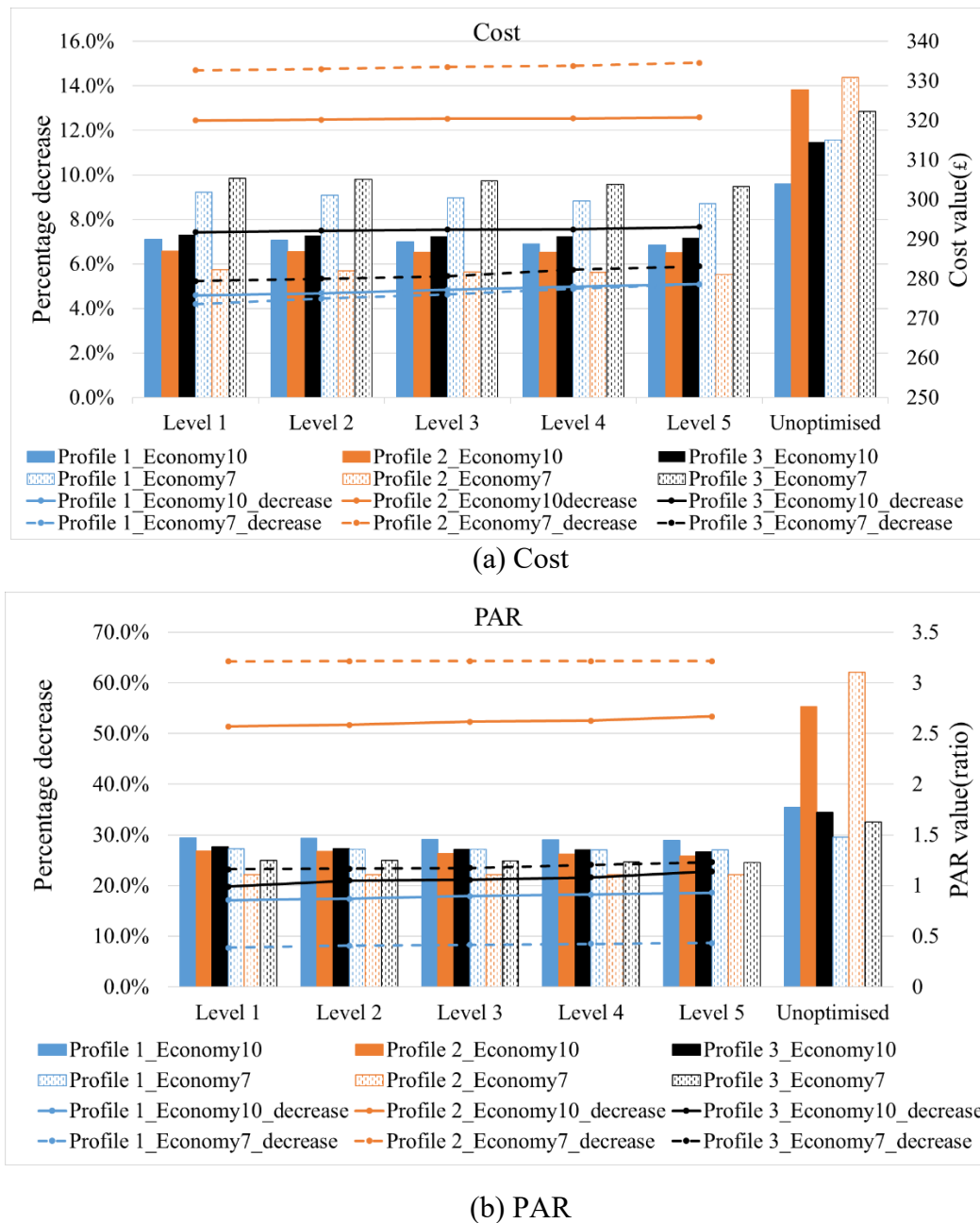


Figure 6.9 The percentage decrease of cost and PAR in the sensitivity analysis

6.5.2.1 Electricity tariffs analysis

Tables 6.5, 6.6 and 6.7 show the results of three initial activity profiles with Level 3 ranges of activity start times and the distribution of off-peak hours in the Economy 7 tariff. These tables suggest a similar finding that the rescheduling of EV charging loads contributes to the major part in the improvement in both cost and PAR.

Table 6.5 Results of Profile 1 “Survey” with Economy 7

Profile 1	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
Indoor activity	Unoptimised	Unoptimised	Unoptimised	Optimised with minimum cost	Optimised with minimum PAR
EV charging	Uncontrolled	“Cost first”	“PAR first”		
Electricity cost (£)					
Value	315.05	302.81	306.92	300.48	301.68
Compared to Stage 1	-	-3.88%	-2.58%	-4.62%	-4.24%
PAR					
Value	1.48	1.39	1.39	1.38	1.36
Compared to Stage 1	-	-6.25%	-6.25%	-6.53%	-8.31%
The average absolute load difference percentage from Stage 1 (per minute)					
Total load	-	12.47%	11.04%	13.79%	13.25%
Indoor load	-	-	-	2.37%	1.72%
EV charging load	-	80.18%	70.95%	79.18%	79.67%

Table 6.6 Results of Profile 2 “Simulated_Normally” with Economy 7

Profile 2	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
Indoor activity	Unoptimised	Unoptimised	Unoptimised	Optimised with minimum cost	Optimised with minimum PAR
EV charging	Uncontrolled	“Cost first”	“PAR first”		
Electricity cost (£)					
Value	330.90	282.48	304.92	281.76	305.45
Compared to Stage 1	-	-14.63%	-7.85%	-14.85%	-7.69%
PAR					
Value	3.10	1.43	1.11	1.44	1.11
Compared to Stage 1	-	-53.88%	-64.22%	-53.58%	-64.30%
The average absolute load difference percentage from Stage 1 (per minute)					
Total load	-	40.71%	33.48%	41.30%	33.69%

Indoor load	-	-	-	0.87%	0.78%
EV charging load	-	200.00%	164.47%	200.00%	163.35%

Table 6.7 Results of Profile 3 “Simulated_Sampled” with Economy 7

Profile 3	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
Indoor activity	Unoptimised	Unoptimised	Unoptimised	Optimised with minimum cost	Optimised with minimum PAR
EV charging	Uncontrolled	“Cost first”	“PAR first”		
Electricity cost (£)					
Value	322.30	305.68	310.79	304.73	310.89
Compared to Stage 1	-	-5.16%	-3.57%	-5.45%	-3.54%
PAR					
Value	1.63	1.26	1.26	1.25	1.25
Compared to Stage 1	-	-22.62%	-22.62%	-23.10%	-23.48%
The average absolute load difference percentage from Stage 1 (per minute)					
Total load	-	18.04%	14.97%	18.47%	15.12%
Indoor load	-	-	-	1.05%	0.97%
EV charging load	-	96.93%	80.48%	96.72%	79.47%

Figure 6.10 shows the results in Tables 6.5, 6.6 and 6.7, illustrating three sets of total load profiles, derived from three initial activity profiles, both before and after DSM optimisation with the distribution of off-peak hours in the Economy 7 tariff.

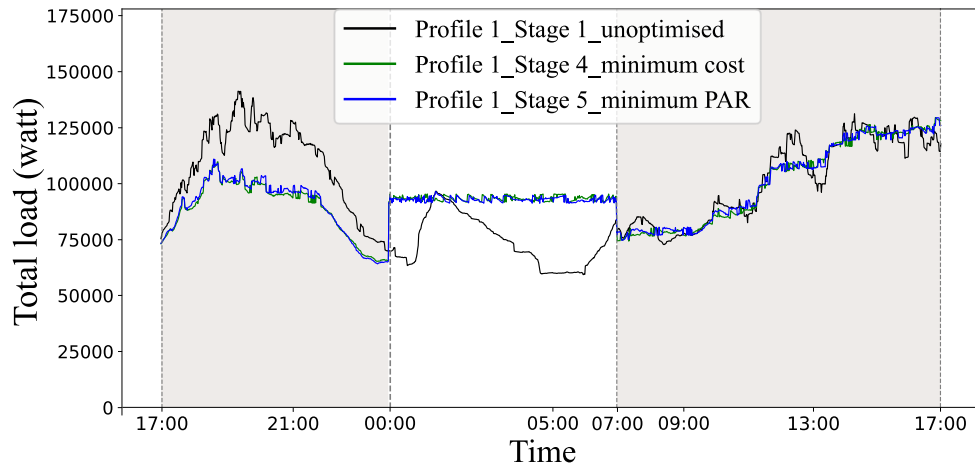
Electricity tariffs impact the indoor load profiles in two ways. First, the electricity price in the tariffs impacts the electricity intensity of indoor activities. For example, if the electricity price increases in the evening when people usually cook meals, people may not change the time of cooking due to relatively inflexible food demand but reduce the electricity consumption by using a microwave instead of an oven. This kind of impact was not captured by most existing DSM research since the electricity intensity of indoor activities in the literature is usually constant. In contrast, this chapter utilises an ML-

based indoor load profile generation model which considers the impact of electricity prices. For example, the unoptimized load value during the off-peak period “20:00-22:00” in Figure 6.8 is higher than the load derived from the same activity profiles but with peak period “20:00-22:00” in Figure 6.10. The unoptimised total load profiles, as the Stage 1 black lines in Figure 6.10, show that the Economy 7 tariff also leads to smaller peak loads due to the long continuous peak hours during the daytime. Consequently, the PARs are lower in the Economy 7 tariff proved by the shorter dashed bars compared with solid bars in the columns “unoptimised” in Figure 6.9 (b). Notably, Profile 2 “Simulated-Normally” is an exception because the peak load was mainly caused by the charging of EVs whose charging rate is irrelevant to the electricity prices.

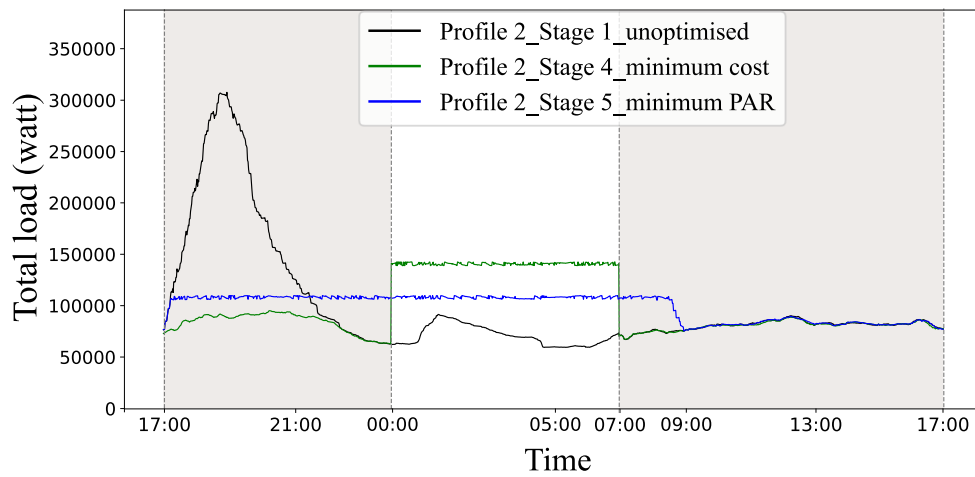
Second, the distribution of off-peak hours in electricity tariffs impacts the activity schedules, which is simulated in most DSM research. In this chapter, this impact is partly shown by the different percentage decreases in cost and PAR due to different distributions of off-peak hours, as represented by the change of line charts in Figure 6.9. Compared with the Economy 7 tariff, the Economy 10 tariff has three more off-peak hours and their distribution is more dispersed. Consequently, the Economy 10 tariff provides more opportunities for rescheduling indoor activities and EV charging, allowing larger cost decreases in Profile 1 “Survey” and Profile 3 “Simulated_Sampled”. However, the dispersed distribution of off-peak hours does not guarantee more improvement. For example, the long continuous off-peak hours in the Economy 7 tariff overlap with the night EV parking time in Profile 2 “Simulated_Normally”, leading to a larger cost decrease compared with the Economy 10 tariff. Notably, since PAR is not directly related to the distribution of off-peak hours, the different percentage decrease in PAR in the two tariffs is probably due to the different initial load profiles.

The bars at five levels of the ranges of activity start times in Figure 6.9 represent the cost and PAR values in the optimisation results, showing the combination of these two ways of impact. For the observed Profile 1, compared with bars of the Economy 7 tariff, the Economy 10 tariff results in lower solid cost bars and higher solid PAR bars. This comparison indicates that the dispersed distribution of off-peak hours in the Economy 10 tariff may contribute to lower electricity costs and higher PAR in the real world. In summary, more off-peak hours and more dispersed distribution of them provide larger cost-saving potential, since only rescheduling indoor activities across the boundary of

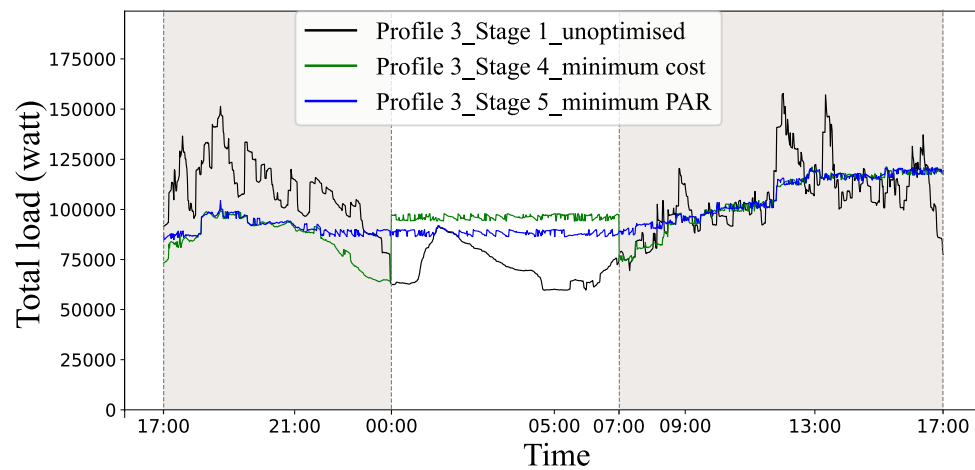
peak and off-peak hours contributes to the reduction of cost. In contrast, long continuous off-peak hours at night may stimulate more PAR reduction. What is more, a more dispersed distribution of off-peak hours may also contribute to peak loads and higher PAR as discussed in the next section.



(a) Profile 1



(b) Profile 2



(c) Profile 3

Figure 6.10 The total load in Stages 1, 4 and 5 with Economy 7

6.6 Discussion

6.6.1 The improvement potential of DSM

One of the main contributions of this chapter is that the comparison result of the three initial activity profiles indicates the exaggerated potential for improvement in DSM in the literature. Since most improvement is achieved by the rescheduling of EV charging, the exaggeration is probably derived from unrealistic EV travel patterns. Normally distributed EV travel patterns result in large charging demand and clustered uncontrolled charging loads, while travel trips sampled from surveys in other contexts demonstrate different travel patterns in terms of trip frequency and timings. Independently simulated EV usage patterns also lose the connection with indoor activities, which further affects the assessment of DSM. While more research is required to validate this conclusion in general contexts, the potential for improvement results presented in this chapter are consistent with the literature as described below.

It is difficult to compare the potential for improvement of DSM across different studies due to their different contexts. These contexts can vary in terms of the availability of EVs, energy storage systems and renewable energy, the size of participants and the electricity tariffs. Despite this challenge, Table 6.8 presents three studies that have similar basic contexts and optimisation objectives to this chapter. This small set of existing studies shows similar or larger improvement than that of Profiles 2 and 3 in this chapter. One explanation is that their indoor activities and EV travel patterns are also simulated based on separated datasets or normal distributions rather than real profiles. In summary, simulated activity profiles can result in a relatively large improvement, while the smaller improvement derived from observed activity profiles requires more validation.

Table 6.8 The improvement achieved in the literature

Reference	Components	Sample size	PAR decrease	Cost decrease
Durillon et al. (2020)	Home appliances and EVs with a penetration rate of 0.15	140 households	21%-31%	-
Nazemi, Jafari &	Home appliances and at least 1 EV for each unit	480 residential units and 20	-	9.91%-23.02%

Zaidan, (2021)		commercial units		
Cerna & Contreras (2021)	Home appliances and an EV for each customer	12 customers	70.14%	31.79%

6.6.2 The contribution of indoor load change and EV load change in DSM

In this chapter, the improvement in cost and PAR is predominantly attributed to the rescheduling of EV charging, rather than to the rescheduling of indoor activities. The substantial contribution of rescheduling EV charging in DSM has been recognised (Sørensen et al., 2021; Chen et al., 2018; Sørensen et al., 2019), but a direct comparison between the contribution of rescheduling indoor activities and EV charging is rare. In addition, the contribution of rescheduling EV charging depends on the travel patterns, the number and battery capacity of EVs, the charging rate and the availability of charging infrastructures. All these influential factors are usually arbitrary in DSM research. A similar conclusion is presented by Nazemi, Jafari & Zaidan (2021) that plug-in EVs (PEV) are the most critical electrical assets for peak shaving. The author argued that PEVs not only consume a huge amount of electricity but also are more flexible with wider charging periods. However, one of its assumptions is that each unit has 1 or 2 PEVs, which may lead to exaggerated EV ownership and associated charging demand.

This chapter estimates the EV charging loads based on the recorded car trips and ownership. The contribution of rescheduling EV charging loads is indicated to be quantitatively greater compared with rescheduling indoor activities. These results are consistent with the previous arguments in the literature but provide more credibility due to the employment of recorded individual activities.

6.6.3 The contradiction between optimising cost and PAR

The percentage decrease in cost and PAR achieved by Stages 4 and 5 shown in Tables 6.2, 6.3 and 6.4 with the Economy 10 tariff indicates the contradiction between optimising cost and PAR. The main reason could be the mismatch between peak hours in electricity tariffs and the period of actual peak loads. For example, the peak loads in Profile 1 occur during the off-peak hours 20:00-22:00 in the Economy 10 tariff, as shown in Figure 6.8 (a). This mismatch may stem from the inaccurate modelling of

activity profiles and energy demand in the design of ToU tariffs. Furthermore, the impact of ToU electricity tariffs and DSM can exacerbate this mismatch and contribute to the contradiction. First, the electricity intensity of indoor activities may reduce during peak hours and relatively increase during off-peak hours. Second, during the process of minimising cost, indoor activities and corresponding loads are shifted from peak hours to off-peak hours. However, this shift inadvertently further increases the mismatched peak loads during off-peak hours and the corresponding PAR. The process of minimising PAR does the rescheduling adversely, which moves mismatched peak loads from off-peak hours to peak hours.

Similar conclusions are not found in the literature as few studies designed these dual objectives and analysed the impact of the distribution of off-peak hours in electricity tariffs. However, Imran et al. (2020) indicated that the DSM optimisation model may generate new peak loads while reducing the current peak loads. One report of Project Low Carbon London (Bilton et al., 2014) also pointed out that if the rescheduling strategy of DSM only avoids the operation of appliances in peak hours, these appliances may be switched on simultaneously after the peak hours and cause new peak loads. These findings may indicate the same contradiction as the cost is reduced by shifting the usage of appliances from peak hours but the new peak loads in off-peak hours could lead to higher PAR.

In addition, this chapter shows that the contradiction can be mitigated by changing the distribution of off-peak hours. The results of Stages 4 and 5 shown in Tables 6.5, 6.6 and 6.7 with the Economy 7 tariff show less contradiction between reducing cost and PAR since original peak loads occur during peak hours and the continuous off-peak hours are long enough to flatly shift peak loads.

6.7 Summary

This chapter designs a hybrid DSM framework to integrate the energy demand modelling framework designed in Chapter 4, the preferred ML-based indoor load generation model indicated in Chapter 5 and an evolutionary multi-objective optimisation algorithm NSGA-II. Therefore, the cohesive activity profiles and various factors that influence energy demand are considered. In addition, this chapter explores the potential for improvement of observed and simulated activity profiles. Five levels

of ranges of activity start times and two distributions of off-peak hours in electricity tariffs are tested for sensitivity analysis. The main conclusions include:

- (1) Three datasets in this chapter suggest the number of daily parking records per vehicle ranges from 1.43 to 1.66. This indicates that the commonly used method for estimating EV charging demand based on empirical probability distributions and average daily driving mileage may introduce bias. Specifically, this method may either overestimate the vehicle number and consequential electricity consumption by about 43% to 66% or lose the information on multiple parking events associated with the same vehicles.
- (2) DSM with survey-sampled EV usage or normally distributed EV usage may exaggerate the potential for improvement in cost and PAR by approximately 2 or 3 times respectively. The activity profile with survey-sampled EV travel patterns achieves results more closely aligned with those of the observed profile. Therefore, EV travel patterns simulated from the same geographical area or even the same population group are recommended in DSM, in cases where real profiles are not available.
- (3) More evidence is provided for the conclusion in the literature that rescheduling EV charging may be a priority in DSM since it provides larger flexible demands (Nazemi, Jafari & Zaidan, 2021). The comparison results in this chapter show that rescheduling EV charging contributes to more than 90% of the cost and PAR reduction. Conversely, rescheduling indoor activities has little impact on DSM and is not sensitive to activity start time ranges.
- (4) The distribution of peak and off-peak hours in electricity tariffs should be designed carefully to avoid the contradiction between minimising cost and PAR. Long continuous off-peak hours at night contribute to a greater decrease in PAR while dispersed off-peak hours throughout the day provide more opportunities to save cost.

This chapter has three main contributions. First, a framework is presented for the assessment of electricity tariffs and DSM. Second, this chapter advances the DSM by incorporating an ML-based load profile generation model, which takes into account multiple factors that influence energy demand. Third, the test of three types of activity profiles demonstrates the exaggerated potential for improvement in DSM. The research presented in this chapter has several limitations, which provide directions for future

work. First, the EV usage in Profile 3 is sampled from the LTDS dataset, which is not in the same context as the observed profile in the METER dataset. People in a large conurbation like London may have different travel patterns from the national average patterns. The impact of this discrepancy on exaggerated potential is not considered. Second, existing research usually assumes a static occupancy schedule, which means participants will not change the time of leaving and returning home in DSM. This assumption is the simplification of real situations while occupancy in real life can change according to charging scenarios (Daina, 2014). Last but not least, the choice of rescheduling indoor activities in DSM was usually simplified as minimising aggregated objectives within activity start time ranges. On the contrary, in the real world, most consumers reschedule activities to improve their own disaggregated utility considering multiple information such as time slots, activity categories, electricity tariffs and socio-economical attributes. These choices in DSM have not been fully understood and studied yet. Therefore, the next chapter will focus on modelling consumers' indoor activity adaptation as the response to time-of-use tariffs in DSM.

Chapter 7

THE CHOICE MODEL OF CHANGING ACTIVITY PATTERNS IN DEMAND-SIDE MANAGEMENT

7.1 Introduction

Previous chapters have demonstrated the application of demand-side management (DSM) in which incentive payments or energy price signals are utilised to promote the adaptation of consumer activity profiles. The objectives of DSM include reducing the peak load, reshaping the load profile and maintaining the energy supply-demand balance. To achieve these objectives, energy price signals are a prevalent tool in DSM and are usually represented by various types of electricity tariffs, including Time-of-use (ToU) and dynamic Time-of-use (dToU). ToU tariffs have been used around the world and two famous examples in the UK, the Economy 7 and Economy 10 tariffs, are offered by several energy providers, e.g., British Gas and Green Energy UK. In the residential sector, the underlying belief is that consumers with ToU or dToU tariffs will reschedule indoor activities from hours with higher rates to hours with lower rates to save energy expenses.

In this context, consumers' responses to price signals greatly influence the efficiency of DSM but have not been fully studied. Most literature focused on designing optimization models assumes that consumers are always rational and economic agents, exhibiting optimal behaviours (Good, 2019). In addition, the optimal behaviours are usually designed by researchers from the standpoint of the grid, the society or the community based on aggregated monetary savings and the flexible range of activity start times. However, individual choices and many other influential factors in consumers' adaptation of activity schedules are neglected, such as the seasons, working days, price levels, original time of activity, the heterogeneity of individuals/households and participants' attitudes toward energy-saving, all of which may cause biased design and assessment of DSM (Good, 2019). Therefore, this chapter introduces choice models to study consumers' indoor activity adaptation in DSM and analyses the influential factors. Mixed logit discrete choice models are built for six common indoor activities based on data collected through stated preference (SP) surveys. In addition, case studies are designed where the estimated choice models are used to predict consumer responses

to different ToU price levels. The findings can help simulate the behaviourally realistic responses of consumers, design proper ToU tariffs, evaluate the real energy-saving potential of DSM and contribute toward energy conservation. Contrary to previous chapters that focus on integrating accurate consumer activities as input in energy demand modelling and DSM, this chapter digs deeper to understand consumer behaviours and choices in DSM. Although the methodologies in this chapter differ from others, this exploratory research aligns with the overarching purpose of improving energy demand modelling and DSM.

The rest of this chapter is organized as follows. Section 7.2 describes the survey design and data collection, as well as presents the results of the exploratory analysis. Section 7.3 describes the structure of choice models and analyses the results. Section 7.4 introduces the case studies and explores the distributional impacts. Section 7.5 discusses special issues in this chapter. Finally, Section 7.6 summarises this chapter.

7.2 Survey design, data collection and exploratory analysis

As stated in Section 3.3.1, an SP survey for demand-side management, DSM-SP, was designed to collect data about consumers' choice of adapting indoor activities in response to ToU electricity prices. This DSM-SP survey was distributed to residents in the UK through a market research company PanelBase in April 2023 with the goal of 1200 completes. This sample size is determined by the rule of thumb because no prior knowledge of the parameters exists. Consequently, the sample size efficiency can not be calculated (Rose & Bliemer, 2013)

7.2.1 Survey Design

The DSM-SP survey collects four categories of data as shown in Figure 3.1 in Section 3.3.1: (a) current activity schedules and tariffs; (b) the choices of adapting indoor activities in hypothetical situations; (c) attitudes toward energy conservation; (d) socio-demographics. At the beginning of the survey, screening questions are asked to make sure that participants are familiar with the context of adapting indoor activities so that the stated responses are as close to real responses as possible. The following exclusion criteria were used to screen out participants:

- (1) Participants are under the age of 18.

- (2) Participants' electricity bill is included in the rent or is a fixed cost regardless of their electricity consumption.
- (3) Participants have not undertaken all of the following six activities at home in the last month, i.e., "Boil drinking water", "Cook hot meals", "Shower", "Use a washing machine", "Work" and "Leisure".
- (4) Participants have difficulty (e.g., physical or mental health conditions) in adapting the aforementioned six activities.

Four contexts are designed for the questions of the first two categories of data: (a) current activity schedules and tariffs and (b) the choices in hypothetical situations of adapting indoor activities. Given that activity schedules and their adaptation can be influenced by seasons and daily working status, the combination of cold/warm season and working/non-working day results in four contexts, i.e., a working day in the cold season, a non-working day in the cold season, a working day in the warm season and a non-working day in the warm season. During the whole survey process, a working day in the cold season is the default context. In addition, participants are also provided with extra questions in the other contexts as necessary, if they state that their responses in any of these other contexts would be different from the default context.

Questions about (c) attitudes toward energy conservation and (d) socio-demographics are designed based on similar questions in the literature (Janmaimool & Chontanawat, 2021; Yilmaz, Weber & Patel, 2019). Details of all questions can be found in Appendix 2 and the result analysis is shown in Section 7.2.2.

7.2.1.1 Current tariffs and activity schedules

Participants in the DSM-SP survey are asked about their current electricity tariffs and their schedules for six common indoor activities. These questions aim to understand the real-world context as current tariffs and activity schedules can influence the choice in hypothetical situations. In addition, the hypothetical situations in the stated choice experiments can be designed based on the current tariffs and activity schedules to avoid unfamiliar or impractical hypothetical settings. For example, participants will be presented with hypothetical situations where the activity is originally undertaken during time periods that are randomly selected based on their reported real-world schedules.

Electricity tariffs can be broadly categorised into Single-rate tariffs and ToU tariffs. Single-rate tariffs have a flat rate for electricity regardless of the time of day while ToU

tariffs have different rates depending on the time of the day. Participants are asked about their electricity tariff type, corresponding price ranges and their certainty of the price ranges. Especially, the DSM-SP survey focuses on a real ToU tariff in the UK: Economy 10, which was also recorded by some of the households in the METER dataset. This ToU tariff has three periods of off-peak hours with lower rates, i.e., midnight – 5 am (off-peak 1), 1 pm – 4 pm (off-peak 2) and 8 pm – 10 pm (off-peak 3). This dispersed distribution of off-peak hours in the Economy 10 tariff provides more opportunities for rescheduling indoor activities from peak hours to off-peak hours compared with the Economy 7 tariff, another real ToU tariff in the UK with off-peak hours from midnight to 7 am. Therefore, the distribution of peak and off-peak hours in the Economy 10 tariff is used in the questions about activity schedules and hypothetical situations.

The following six household activities are chosen for the DSM-SP survey since they are commonly reported in time-use surveys (Grünewald et al., 2017; Morris et al., 2016) and are widely used as flexible activities in DSM (Goyal & Vadhera, 2021; Bissey, Jacques & Le Bunetel, 2017; Bilton et al., 2014; Nazemi, Jafari & Zaidan, 2021). Participants are asked about their typical duration of undertaking these activities during the peak hours in the Economy 10 tariff and their weekly frequency.

- (1) Cook hot meals (e.g., use electric hobs, microwave and electric oven);
- (2) Boil drinking water (e.g., use electric kettles);
- (3) Shower (e.g., use electric showers);
- (4) Use a washing machine;
- (5) Work with electrical appliances(e.g., laptop);
- (6) Leisure with electrical appliances(e.g., TV).

The adaptation of EV charging is not considered in this chapter since it has been partly studied in Daina (2014) and its inclusion could complicate the hypothetical situations by introducing additional factors such as occupancy schedules and travel patterns. These questions about current indoor activity schedules are firstly asked in the default context of a working day in the cold season and then participants can choose whether to provide different answers in other contexts. An example of the questions about indoor activity schedules is shown below:

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On a **working day**  in the **cold season** , e.g., from December to February, or the average low temperature is about or below 2°C (35.6°F),

for each activity type below, during which time periods do you usually undertake it at home (multiple choice) and what's the frequency (per week) and duration (during each episode)?

Example: If you usually cook hot meals for 10 mins at 8 am and 25–40 mins at 7 pm every working day and you have 5 working days a week, you can enter like the example in the first row.

	Peak hours 05:00–13:00	Peak hours 16:00–20:00	Peak hours 22:00–24:00	Other non- peak hours	How many times do you undertake the activity per week (consider only working days)
	Typical duration(min)	Typical duration(min)	Typical duration(min)	Typical duration(min)	Please input the number
<i>Example 1: Cook hot meal</i>	10	25–40			10
Cook hot meals					
Boil drinking water					
Shower					
Use a washing machine					
Work with electric appliances					
Leisure with electric appliances					

Figure 7.1 Questions about current tariffs and activity schedules

If participants currently have ToU tariffs, an additional question is presented regarding their previous experience of switching from a single rate tariff to the ToU tariff. If such a switch has occurred, further questions are asked about whether and how they adapted each of the six activities of interest during this switch. These questions are essentially like a revealed preference survey to record real-world responses to ToU tariffs.

7.2.1.2 Design of the stated choice experiments

The electricity prices in the stated choice experiments (SCEs) are designed based on the news that starting from 1st October 2022, the Energy Price Guarantee raised the Electricity Price Cap from 28 pence/kWh to 34 pence/kWh in the UK. Therefore, in hypothetical situations, the increasing single rate promotes the switch to a ToU tariff with fixed peak and off-peak hours. The peak rate at different hypothetical tasks in the SCEs ranges from 26.46 to 41.58 pence/kWh and the off-peak rate varies between 11.34 and 34.02 pence/kWh. The off-peak rate is set to be always lower than the peak

rate. Examples of peak hours, off-peak hours and two potential ToU tariffs are shown below:

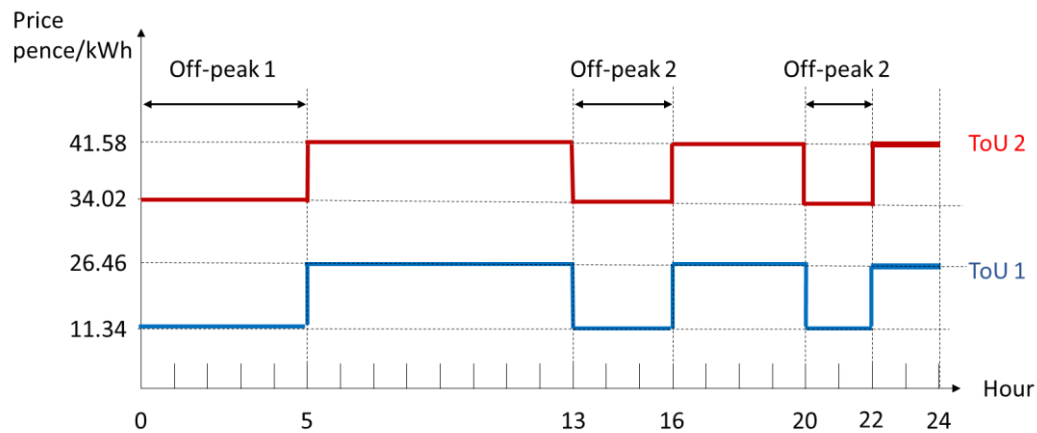


Figure 7.2 Examples of ToU tariffs

Due to the switch of tariffs in the hypothetical choice situations, participants are asked to choose among the following three alternatives for adapting a certain type of activity schedule during peak hours. This activity is chosen from the six common activities previously mentioned and the original peak hour period is selected from the Economy 10 tariff based on the corresponding activity schedule reported by the participant.

(1) Alternative A: “Reschedule”

Description: Reschedule the activity from peak hours to off-peak hours.

Example: change the timing of cooking a hot meal from 7 pm (peak hours) to 9 pm (off-peak hours).

(2) Alternative B: “Reduce/drop”

Description: Reduce the electricity intensity of the activity or drop the activity during peak hours.

Example: Use the microwave (less energy-intensive) instead of electric hobs when cooking a hot meal at 7 pm (peak hours), or order food delivery instead of cooking a hot meal.

(3) Alternative C: “No change”

Example: Still cook a hot meal at 7 pm (peak hours).

Alternatives are characterised by the following attributes in the SCEs:

- (1) Rescheduled time: The off-peak hours in the Economy 10 tariff, to which the activity is rescheduled. This is specific to Alternative A “Reschedule”.

(2) Monetary value change:

- Saving (“Willingness to Accept”): The saving on electricity bills by choosing the alternative compared with Alternative C “No change”; Or
- Payment (“Threshold”): The amount charged to consumers for the electricity consumed by undertaking the activity.

This applies to all the alternatives.

These two measures of value change, i.e., saving and payment, are designed based on prospect theory. This theory indicates that two typical welfare measures, Willingness to accept (WTA) or incentives and Willingness to pay (WTP) or disincentives, with the same value changes, can have different impacts (Koetse & Brouwer, 2016). In the DSM-SP survey, value change in the alternatives can be described naturally with the concept of WTA, which is the saving accepted as compensation for changing the original activity schedules. On the other hand, WTP, which is the extra payment to obtain more benefits, is not easily applicable to this study context as the reference situation with the least payment is hard to determine. Therefore, compared to the saving, the payment and loss is referred to as the “Threshold”, which measures the maximum payment that participants will be willing to make after adapting their original activity schedule. An example of the hypothetical situation is shown in Figure 7.3. Twelve blocks of hypothetical situations are designed to cover the adaptation of the six common activities and two ways of measuring value changes.

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Context:

- **Date and season:** On a typical working day  during the cold season .
- **Activity and time:** you usually undertake the activity "Leisure with electric appliances"  during the Morning peak 05:00-13:00.
- **Electricity tariff:** You switch to a Time of Use tariff with a peak rate of 41.6 pence/kWh and an off-peak rate of 34.0 pence/kWh.

Scenario:

Which of the following alternatives (A, B, C) would you choose?

Activity: "Leisure with electric appliances"

	A	B	C
Action	Reschedule the activity	Reduce the intensity or drop the activity	Not change
Time	To Off-peak hours, 20:00 – 22:00	During <u>Morning peak 05:00-13:00</u>	During <u>Morning peak 05:00-13:00</u>
Saving	1.68 £/month 20.14 £/year	6.46 £/month 77.54 £/year	0

A
☐

B
☐

C
☐

Figure 7.3 Hypothetical situation of activity adaptation

The alternatives and influential attributes in the SCE design are presented in Table 7.1.

Table 7.1 Alternatives and influential attributes in the SCE design

		Alternatives		
		A. “Reschedule “	B. “Reduce/Drop”	C. “No change”
Attributes		Attributes levels		
In context	Season	Cold, warm		
	Date	Weekday, weekend		
	Activity types	(1) Cook hot meals (e.g., use electric hobs, microwave and electric oven) (2) Boil drinking water (e.g., use electric kettles) (3) Shower (e.g., use electric showers) (4) Use a washing machine (5) Work with electrical appliances(e.g., laptop) (6) Leisure with electrical appliances(e.g., TV)		
	Original activity time	According to the reported activity schedule		
	WTA/Threshold	(1) Saving (2) Payment		

In alternatives	Rescheduled time	Off-peak1, Off-peak2, Off-peak3	-	-
	Electricity consumption ratio	-	0%, 30%, 60%	-
	The percentage increase in peak price	-	+40%, +80%, +120%	-
	Percentage difference between peak and off-peak price	40%, 80%, 120%	-	-
	Value change	Calculated	Calculated	Calculated

The statistical design of the stated choice experiments involves designing different levels of attributes for alternatives in choice situations. In the DSM-SP survey, the peak price, off-peak price and the electricity consumption of the activity determine the savings or payments for Alternative A “Reschedule”. Similarly, the peak price and the gap between the original electricity consumption and the new electricity consumption of the activity are determining factors for Alternative B “Reduce/Drop”. Lastly, the peak price and the electricity consumption of the activity influence the payment for Alternative C “No change”. Due to this complex correlation, generating different levels of savings or payments directly by efficient design is at risk of inferring unreasonable tariffs. For example, the peak price inferred from the designed saving of Alternative B “Reduce/Drop” may be lower than the difference between the peak and off-peak price inferred from the designed saving of Alternative A “Reschedule”. On the other hand, since the peak price should be the same across alternatives in one choice situation, it cannot be set at different levels in multiple alternatives.

Consequently, three price-related attributes that are specific to single alternatives are utilised in the statistical design.

- (1) Alternative A “Reschedule” - The percentage difference between peak and off-peak prices (relative to the fixed price).
- (2) Alternative B “Reduce/Drop” - Electricity consumption ratio: the ratio of the new electricity consumption to the original electricity consumption.
- (3) Alternative B “No change” - The percentage increase of peak price (relative to the fixed price).

The fixed price of single rate tariffs is set as 0.189 £/kWh, reflecting the average domestic variable electricity unit price in the UK in 2021⁴. The three levels, i.e., 40%, 80% and 120%, of the percentage increase of peak price and the percentage difference are designed to generate peak rates between 26.46 and 41.58 pence/kWh and the off-peak rate between 11.34 and 34.02 pence/kWh, which are close to or beyond the real rate in the UK⁵. The household monthly electricity consumption of activities and related appliances is extracted from the Household Energy Survey (HES, stated in Section 3.2.3) as shown in Table 7.2. These electricity consumption patterns of appliances are utilised as the benchmark for calculating the savings and payments associated with alternatives. This chapter assumes linear relationships between activity and monthly electricity consumption. One reason for this approach is that the nonlinear relationship between activity and electricity consumption has been partly integrated into the nonlinear choice selection probabilities. Additionally, using SP methods to study activity adaptation behaviours is the first step in this exploratory research and the assumption of linear relationships for monthly aggregated electricity consumption is not expected to hugely impact the study of consumer preference and the willingness to pay values.

Table 7.2 Electricity consumption of appliance groups

Appliance group	Average electricity consumption per month (kWh)
Kettle	22.50
Cook	40.71
TV	44.40
ICT	22.95
Shower	25.67
Washing machine	14.35

The prior utilities of alternatives are as shown below:

$$U_A = ASC_A + \beta_{OffPeakHour1} \cdot T_{OffPeakHour1} + \beta_{OffPeakHour2} \cdot T_{OffPeakHour2} + \beta_{PriceDifference} \cdot R_{priceDifference} \quad (7.1)$$

$$U_B = ASC_B + \beta_{ElectricityRatio} \cdot R_{ElectricityRatio} + \beta_{PeakPrice} \cdot P_{PeakPrice} \quad (7.2)$$

⁴ Average unit costs and fixed costs for electricity for UK regions (QEP 2.2.4) <https://www.gov.uk/government/statistical-data-sets/annual-domestic-energy-price-statistics>

⁵

https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1107499/quarterly_energy_prices_uk_september_2022.pdf

$$U_C = 0 \quad (7.3)$$

where ASC denotes the alternative specific constant, β denotes the consumers' sensitivity to attributes, $T_{OffPeakHour1}$ and $T_{OffPeakHour2}$ are the dummy variable which equals 1 if the activity is rescheduled to off-peak 1 or off-peak 2 in Alternative A "Reschedule", $R_{priceDifference}$ is the ratio of the difference between peak and off-peak prices to the fixed rate, $R_{ElectricityRatio}$ is the ratio of the new electricity consumption of the activity to the original electricity consumption in Alternative B "Reduce/Drop".

Six choice situations are designed by Ngene (ChoiceMetrics, 2021). The generated levels of attributes are checked to avoid dominant alternatives and unreasonable tariffs. Walker et al. (2018) proved that prior parameters can greatly improve the efficient design only with great certainty on the prior knowledge. Since this is a novel study that is among the first to introduce the choice model into activity adaptation in the energy domain, prior knowledge of the parameters does not exist. Walker et al. (2018) also posited that implementing two-stage designs that first use a small sample to estimate priors is not robust relative to uninformative designs. Therefore, although the survey went through a soft launch with limited participants, the results from this "prior study" were used to verify the feasibility and the values of prior parameters were set close to zero as in the literature (Manca et al., 2021).

In summary, participants were evenly distributed to one of twelve blocks and each block corresponds to one activity type and one way of measuring value change (i.e., saving or payment). Within each block, one set of six choice situations is first presented in the default context of a working day during the cold season. If the participant indicates another context where their responses are most likely to be different, another set of six choice situations in the indicated context is presented. In other words, choice situations in up to two contexts rather than all four contexts are presented to participants to avoid fatigue.

7.2.2 Exploratory analysis

The online survey was distributed to 3228 individuals in the UK. About 19.05% of these people responded that they were unable to adapt the schedules of those six common activities and then were screened out at the beginning of the DSM-SP survey.

Since participants were recruited by a market research company, researchers have limited access to the information of participants who were screened out. One type of available information is the age group. As shown in Figure 7.4, around 30% of participants aged below 44 years old reported such inflexibility, a higher percentage than those aged above 44 years old. A potential reason might be that people under 44 years old have to allocate more time to work and family responsibilities.

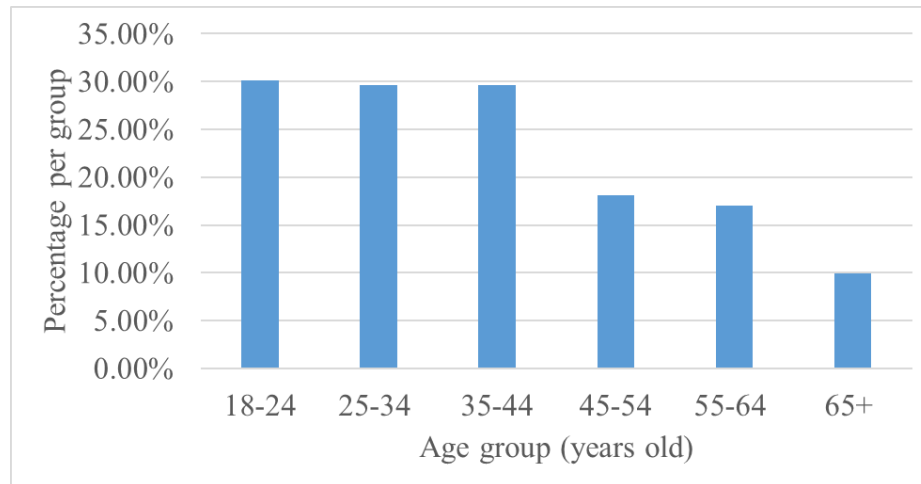


Figure 7.4 The percentage of participants who reported inflexibility

After removing unfinished, unapproved and screen-out replies, about 1333 replies from participants remained.

7.2.2.1 Socio-demographics

Table 7.3 shows the comparison between the socio-demographics of participants in the DSM-SP survey and the United Kingdom Time Use Survey (UK TUS 2014-2015) as introduced in Section 3.3.5. In general, socio-demographic distributions between these two datasets are broadly similar. Due to the screening questions about working status and electricity bills, adults aged between 35 and 44, and participants with full-time work and higher income are over-represented in the DSM-SP survey.

Table 7.3 Summary of socio-demographics

Item	Details	All participants in the DSM-SP survey	Participants with ToU tariffs (191) in the DSM-SP survey	Participants from UK TUS 2014-2015
Gender	Male	41.09%	53.92%	48.33%
	Female	58.61%	45.57%	51.67%
Age	< 18	-		21.88%

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	18-24	4.87%	7.33%	8.37%
	25-34	14.90%	15.71%	12.61%
	35-44	21.78%	20.42%	12.45%
	45-54	19.99%	20.94%	14.28%
	55-64	19.69%	17.28%	11.93%
	65+	18.79%	18.32%	17.00%
Country of residence	England	83.46%	87.96%	84.98%
	Wales	4.57 %	3.66%	4.73%
	Scotland	10.55%	6.81%	7.00%
	Northern Ireland	1.42%	1.57%	3.30%
Employment	Working full-time	47.68%	51.83%	25.94%
	Working part-time	18.49%	18.32%	9.65%
	Unemployment and looking for work	2.77%	3.14%	2.27%
	A homemaker or a stay-at-home parent	6.59%	3.66%	3.60%
	Student	2.47%	3.66%	3.82%
	Retired	18.94%	18.32%	17.11%
	Other	3.07%	1.57%	37.61%
Annual household Income	Less than £20,000	16.32%	16.23%	24.33%
	£20,000 - £40,000	33.98%	34.55%	31.10%
	£40,000 - £60,000	22.31%	20.42%	12.36%
	£60,000 - £80,000	12.43%	12.57%	5.18%
	£80,000 - £100,000	4.49%	4.71%	1.65%
	£100,000 or more	3.89%	6.28%	2.76%
	Prefer not to answer	6.59%	5.23%	24.88%
Number of children (under 18 years old) living with	0	68.56%	64.92%	54.85%
	1	13.92%	18.85%	16.29%
	2	12.65%	10.47%	19.16%
	3 or more	4.87%	5.76%	9.71%
Number of adults in the households	1	33.83% (from 18 to 60 years old)	34.03% (from 18 to 60 years old)	17.34%

	2	28.57% (from 18 to 60 years old)	25.65%(from 18 to 60 years old)	55.36%
	3	26.87% (from 18 to 60 years old)	32.46%(from 18 to 60 years old)	15.84%
	4 or more	10.63% (from 18 to 60 years old)	7.85%(from 18 to 60 years old)	11.46%
Number of older adults (60 years old and above) living with	0	70.13%	69.63%	-
	1	20.51%	21.99%	-
	2	9.28%	8.38%	-
	3 or more	0.07%	0.00%	-

Unique socio-demographic features observed in the DSM-SP survey are summarised in Table 7.4. The results show a prevalent trend of “working from home”, as about 22.59% (8.33%+5.25%+4.58%+4.43%) of participants reported that they work from home more than one day per week. This figure exceeds the proportion of individuals (19.73%) who work outside the home five days per week. Among the 66.02% of participants who answered questions about equipment ownership, more than half (58.01%) own smart meters. This figure is slightly higher than the statistics in Great Britain at the end of June 2022 (52%) (Mita Kerai, 2022). The flexible work schedule and high penetration rate of smart meters provide more opportunities for the implementation of DSM.

Table 7.4 Extra socio-demographics in the DSM-SP survey

Features	Values/levels		Proportion
Number of working days in a week: (Response rate: 99.78%)	Away from home	From home	
	0	0	25.88%
	5	0	19.73%
	0	5	8.33%
	0	7	5.25%
	3	2	4.58%
	2	3	4.43%
	Other		31.80%
Type of the property participants live in	Flat or apartment		17.51%
	Semi-detached house or terraced house		54.71%

	Detached house, cottage or bungalow	27.25%
	Other	0.52%
Who owns the property that participants live in	Owned by participants, partly or wholly	65.72%
	Owned by another family member(s) or relatives	7.26%
	Rented	26.87%
	Other	0.15%
Ownership of equipment (Response rate: 66.02%)	Electric car	5.39%
	Electric scooter	3.07%
	Renewable energy generators (e.g., solar panels)	8.91%
	Energy storage systems (e.g., home battery)	3.29%
	Smart meter	58.01%

7.2.2.2 Electricity tariff

Electricity tariff plays an important role in the adaptation of activities. Most recruited participants (91.24%) paid their electricity bill by themselves, partly or wholly, according to how much electricity they consumed. This high percentage may suggest a high sensitivity to electricity prices. The penetration rate of ToU tariffs is low (14.30%) compared with a high penetration rate of single-rate tariffs (77.10%). In addition, a small percentage of participants are unsure about their tariff (8.6%). The 14.30% penetration rate of ToU tariffs in this DSM-SP survey is slightly higher than the 12% penetration rate of ToU tariffs in DESNZ (formerly BEIS) Public Attitudes Tracker, Spring 2023, UK (Department for Energy Security and Net Zero, 2023). About 36.13% to 37.17% of the participants with the ToU tariff are not sure about their peak or off-peak price, while the percentage of participants with the single-rate tariff who are not sure is 46.99%. Table 7.3 shows that the socio-demographics of these participants with ToU tariffs have no significant difference from those without. The distribution of electricity prices of participants is shown in Figure 7.5. Despite the high percentage of “not sure” responses, the difference between peak price (ToU), offpeak price(ToU) and single rate price is distinctive.

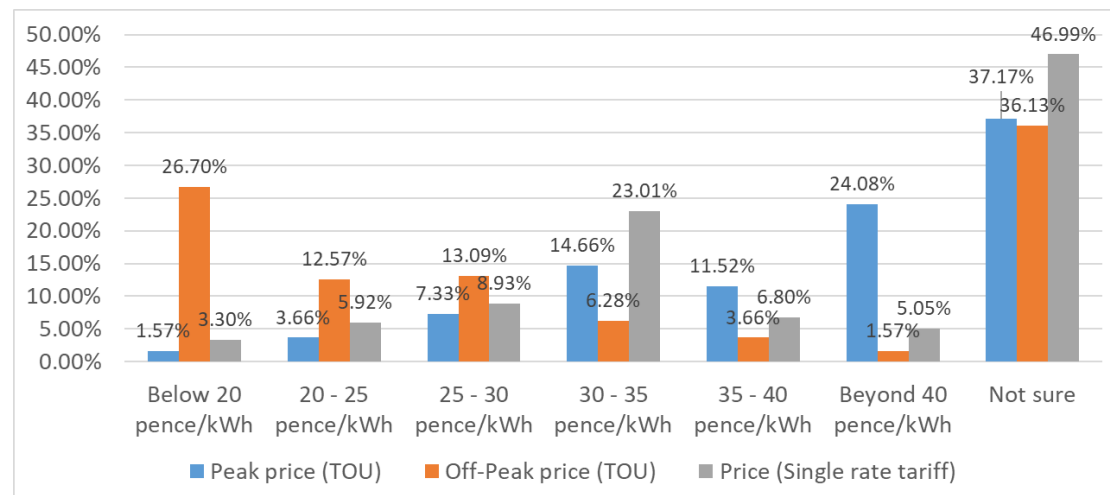


Figure 7.5 Distribution of price rates

More questions were asked to the 191 participants with ToU tariffs to understand their experience of switching from single-rate tariffs and the consequent adaptation of indoor activities. Surprisingly a large percentage of participants with ToU tariffs do not have the experience of switching from single-rate tariffs (74.87%). One potential reason is that households may simply not remember the experience if they switched to it a long time ago, given that the Economy 7 tariff was first introduced around 1978. Another explanation is that they do not pay attention to it when moving to new properties with ToU tariffs or accepting offers from energy suppliers. This oversight may occur because off-peak hours in ToU tariffs (e.g., Economy 7 tariff) typically cover the night period and do not disturb their daytime schedule. Among the 191 participants with ToU tariffs, the experience of switching tariffs does not significantly influence their selection of alternatives in the hypothetical experiments. For the 48 participants that had (or recall) the experience of switching from single-rate tariffs to ToU tariffs, their adaptations of activities are shown in Figure 7.6. About half of the participants in this context did not change the patterns of five common activities after the switch. The only exception is that more participants changed their usage patterns of washing machines than participants who did not. Another finding is that compared with rescheduling the activity to off-peak hours, participants prefer to reduce the energy intensity of the activity or drop it.

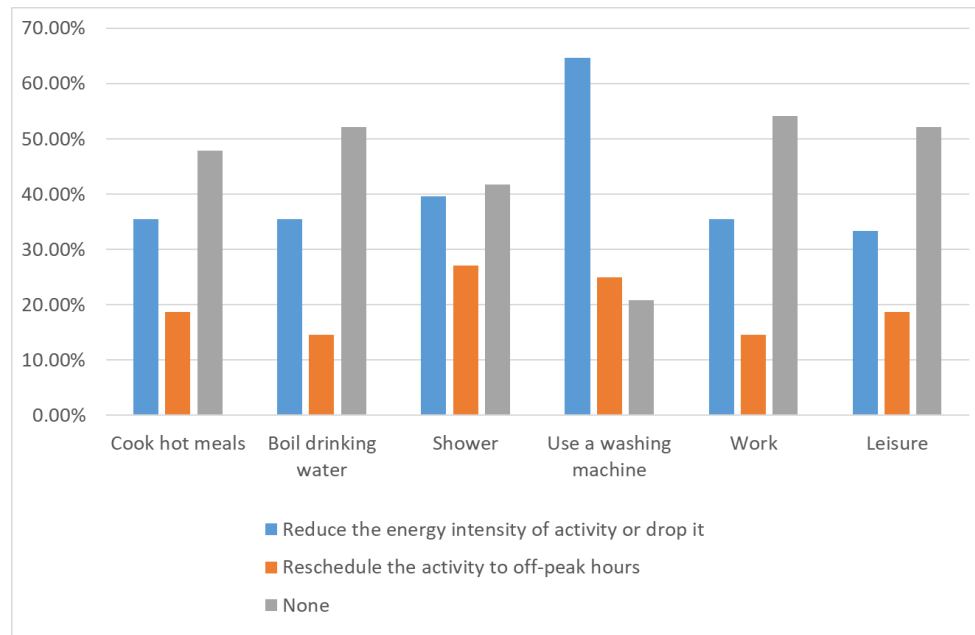


Figure 7.6 Stated activity adaptation after switching to ToU tariffs

7.2.2.3 Activity schedule

The DSM-SP survey asked participants about the duration range of the six common activities during peak and off-peak hours, getting a response rate of about 65% to 88%. The current activity schedules of participants are discussed in three parts in this subsection: (a) probability and probability density distribution during the day; (b) weekly frequency and (c) duration distribution.

7.2.2.3.1 Probability and probability density distribution during the day

The probability profiles of activities show the probability of the activity happening at each time slot, which are the popular outputs of time-use surveys. On the contrary, this DSM-SP survey asked participants “For each activity type below, during which time periods do you usually undertake it at home”. Therefore, one output of these questions is the probability density distribution of the activity during the day under the condition that this activity happens. Despite the difference between probability profiles from time-use surveys and probability density distribution profiles from the DSM-SP survey, they can be compared to show when the activity is likely to happen during the day.

UK TUS 2014-2015 recorded activities that were undertaken every 10 minutes and the probability of activities over the course of the day can be compiled from this. Since the UK TUS does not record the same activity categories as the six common activities in

the DSM-SP study, we use a mapping between similar categories as shown in Table 7.5.

Table 7.5 Activity types in DSM-SP survey and UK TUS

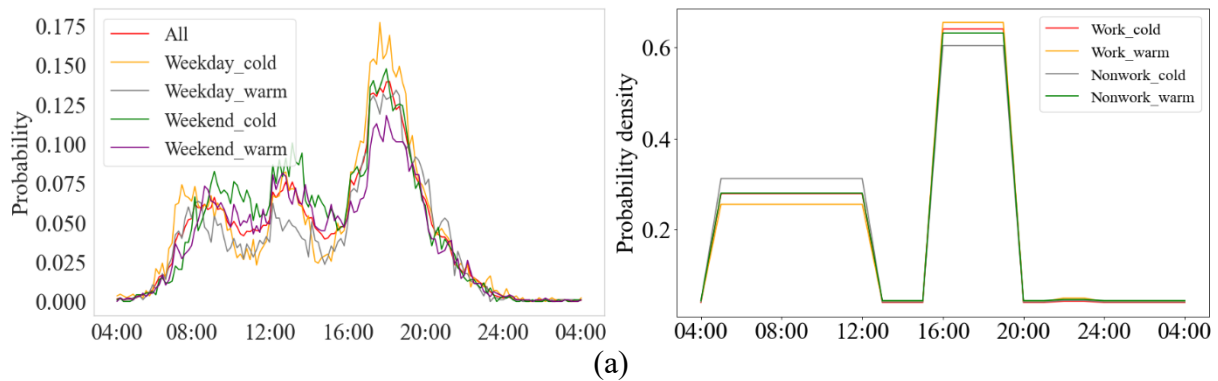
Category	UK TUS 2014-2015	DSM-SP survey
(a)	Food management, including food preparation and baking, and preserving.	Cook hot meals (e.g., use electric hobs, microwave and electric oven)
(b)	-	Boil drinking water (e.g., use electric kettles)
(c)	Personal care	Shower (e.g., use electric showers)
(d)	Laundry, Making and caring for textiles	Use a washing machine
(e)	Main job and Second job	Work with electrical appliances (e.g., laptops)
(f)	TV and Video, and Radio and music	Leisure with electrical appliances(e.g., TV)

Then the probability of activities at home over the day in UK TUS 2014-2015 and the probability density profiles of the corresponding activity from the DSM-SP survey are compared in Figure 7.7. While similar profiles of activities are shown, one exception is “personal care” in the UK TUS in Figure 7.7 (c) which shows an extra peak in the evening due to the inclusion of other activities such as “wash and dress”. In the legend, “Work_cold” means working days in the cold season (January, February and December) and “Nonwork_warm” refers to non-working days in the warm season (June, July and August). The following issues are found through comparison:

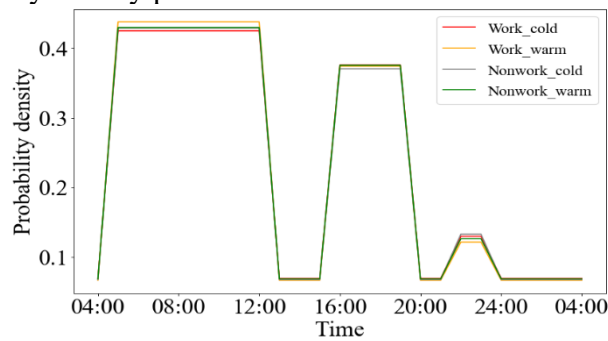
- (1) Different contexts have less impact on the activity schedules in the DSM-SP survey. One fairly obvious reason could be non-response due to the fatigue of repetitive questions in different contexts, which was anticipated.
- (2) Subfigures on the left of Figure 7.7 show that “Weekdays” and “Weekend” are the significant influential factors for the activity schedules in UK TUS. For example, activities (a) food management and (c) personal care are conducted earlier on weekdays, while activities (d) laundry and (f) TV occur more frequently on the weekends.
- (3) Additionally, there is no surprise that the probability of activity “Work” in Figure 7.7 (e) in UK TUS varies across contexts and more “Work” happens on weekdays. Notably, the probability of activity “Work” on weekdays in cold

seasons is distinctively higher than that in warm seasons. Another interesting finding is that during the weekends, the activity “Work” is more engaged in the afternoon during cold seasons, whereas the preference shifts towards the morning in warm seasons.

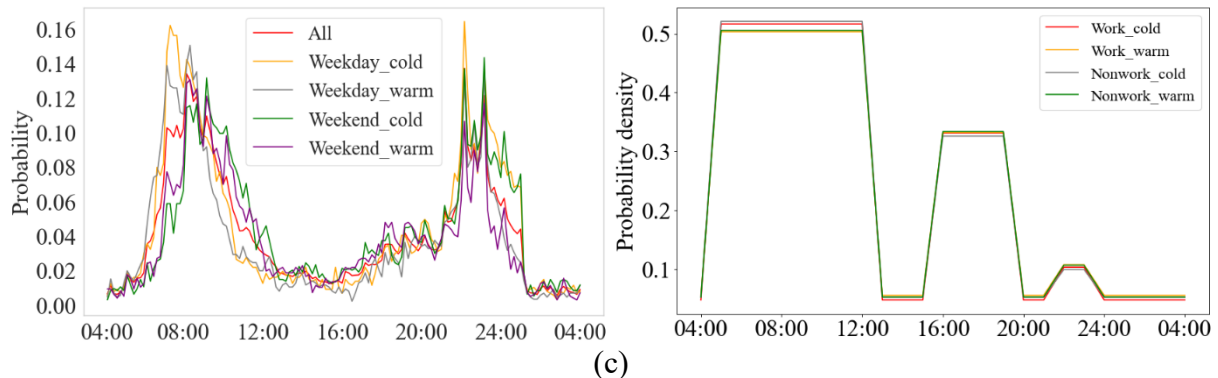
- (4) The peaks in both probability and probability density profiles show most activities are more likely to happen during the peak hours in the Economy 10 tariff, i.e., 5 am-1 pm, 4 pm-8 pm and 10 pm-midnight. This pattern presents both opportunities and challenges for DSM.



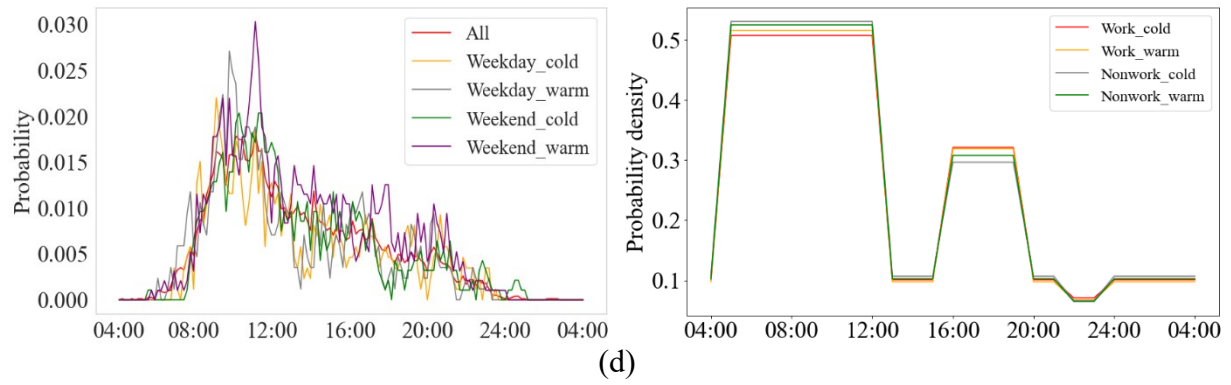
Left: Probability profile of “Food management” in UK TUS
Right: Probability density profile of “Cook hot meals” in the DSM-SP survey



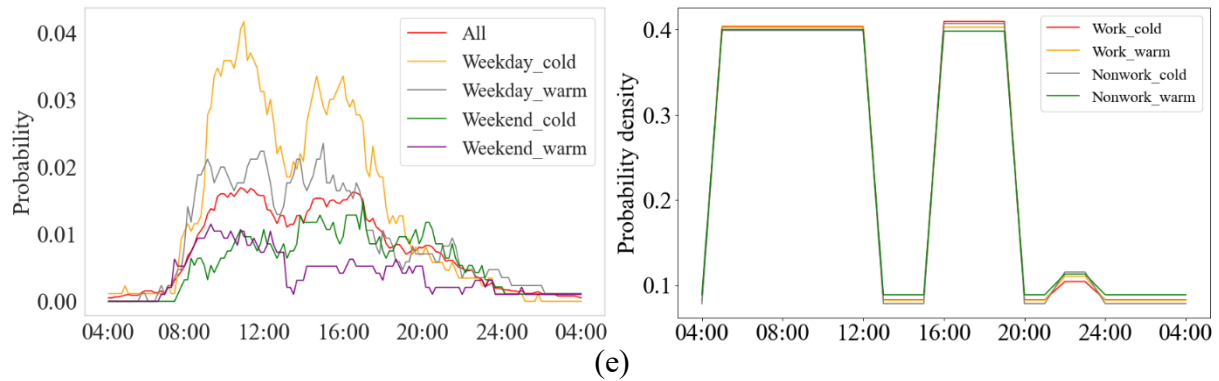
Probability density profile of “Boil drinking water” in the DSM-SP survey



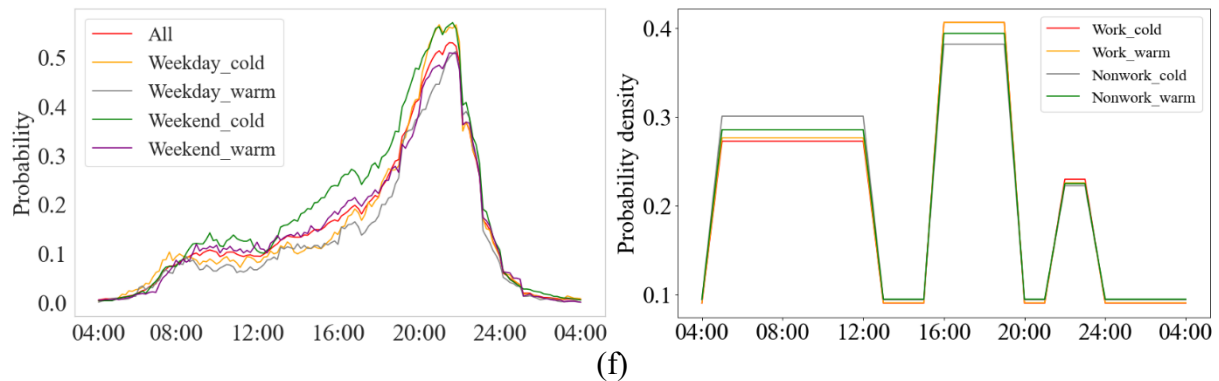
Left: Probability profile of “Personal care” in UK TUS
Right: Probability density profile of “Shower” in the DSM-SP survey



(d)
Left: Probability profile of “Laundry” in UK TUS
Right: Probability density profile of “Use a washing machine” in the DSM-SP survey



(e)
Left: Probability profile of “Work” in UK TUS
Right: Probability density profile of “Work” in the DSM-SP survey



(f)
Left: Probability profile of “TV, radio and music” in UK TUS
Right: Probability density profile of “Leisure” in the DSM-SP survey

Figure 7.7 Activity schedules

7.2.2.3.2 Weekly frequency

The weekly frequency of activities is shown in the box plot in Figure 7.8 with a response rate range from 65.49% to 76.95%. The median frequencies of activities “Cook hot meals”, “Shower”, “Work” and “Leisure” range between 7 and 14, indicating that these activities are undertaken once or twice a day. On the other hand, “Boil drinking water” can occur multiple times a day while “Use a washing machine” could take place once

or twice a week. The primary impact of the seasonal factor is that people tend to have more “Boil drinking water” activity in the cold season.

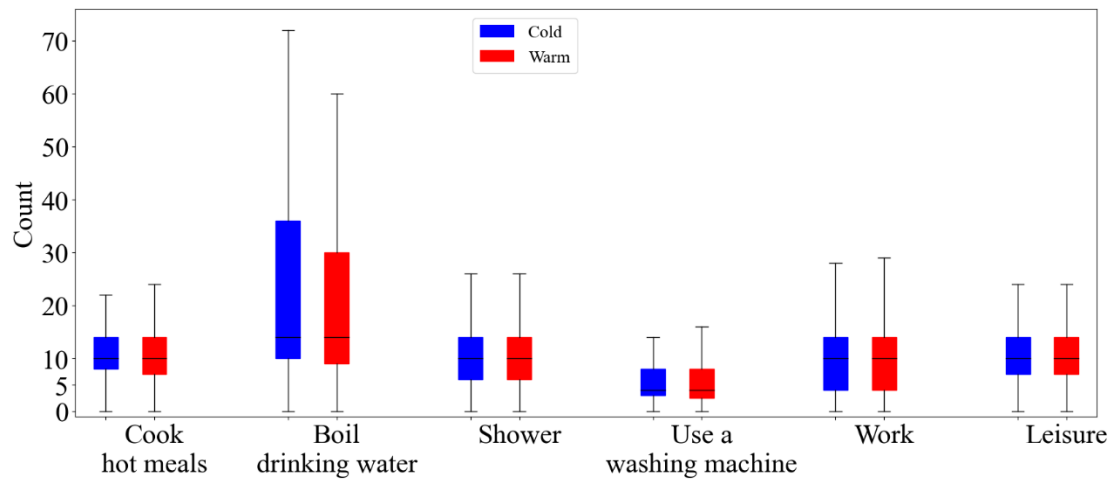
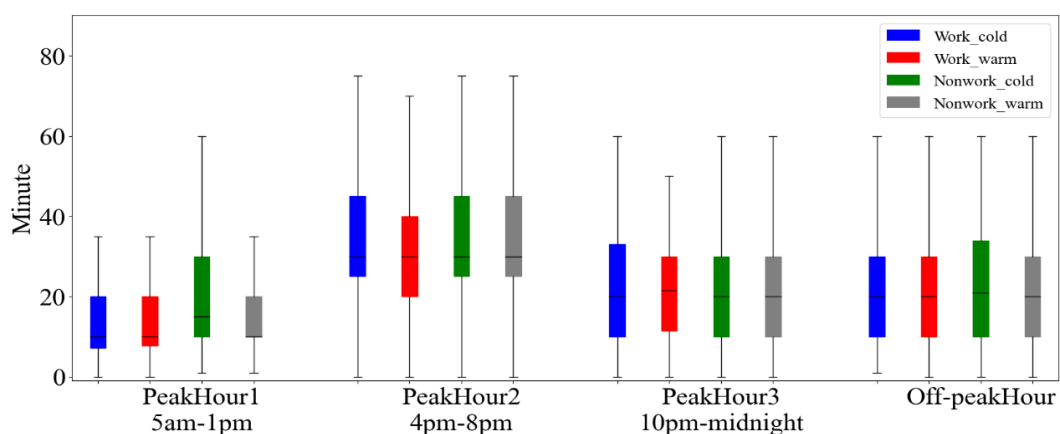


Figure 7.8 Weekly frequency of activities

7.2.2.3.3 Duration distribution

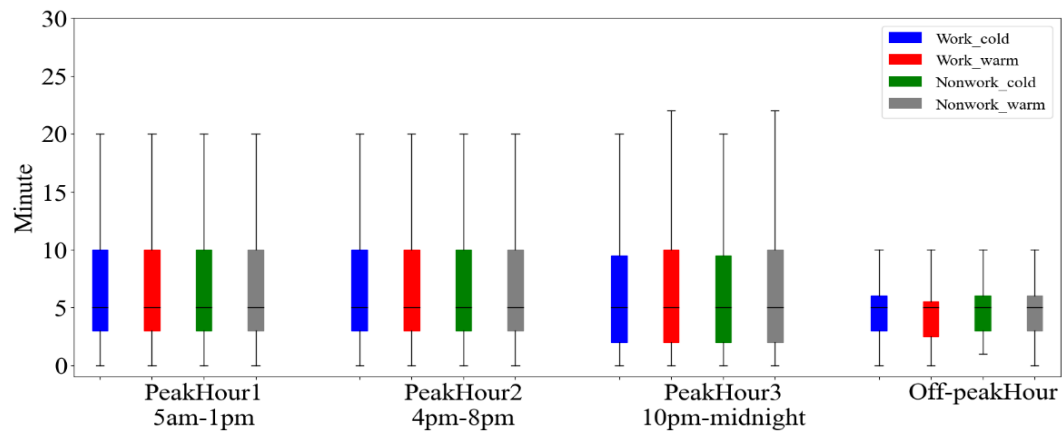
The duration of activities in different periods is shown in box plots in Figure 7.9 with the following findings:

- (1) The duration of (a) “Cook hot meals” is the most volatile and people spend slightly more time on it on non-working days, cold seasons and peak hours 2.
- (2) As expected, the durations of (e)“Work” and (f)“Leisure” are highly related to working/non-working days. Slightly more leisure time is observed in the cold season.

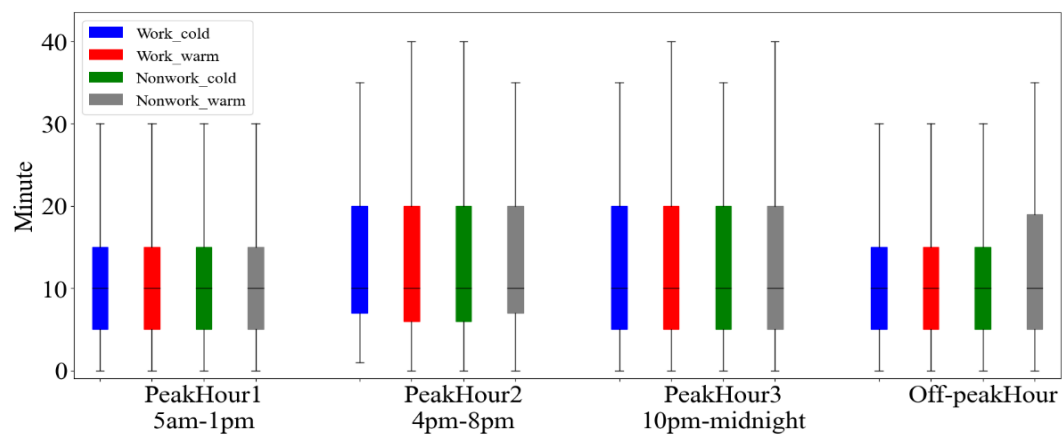


(a) Cook hot meals

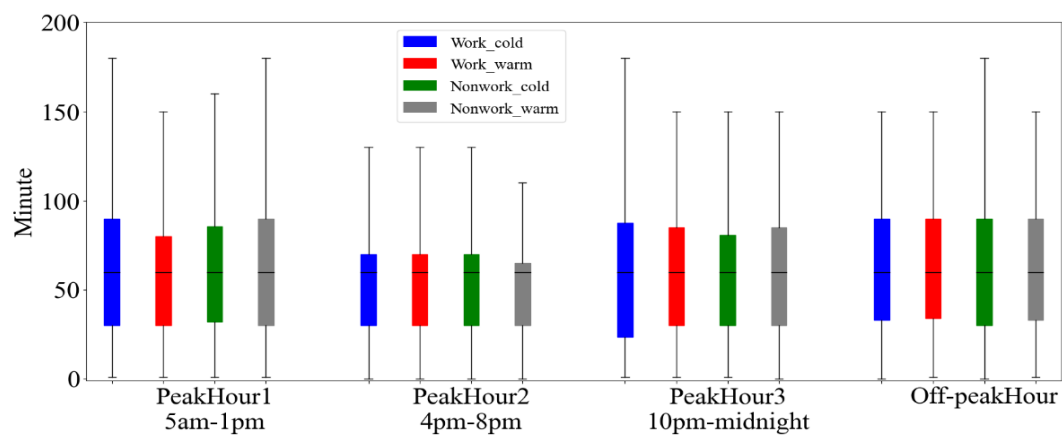
Energy Demand Modelling and Demand-Side Management with Detailed Representation of Consumer Activities and Behaviours



(b) Boil drinking water



(c) Shower



(d) Use a washing machine

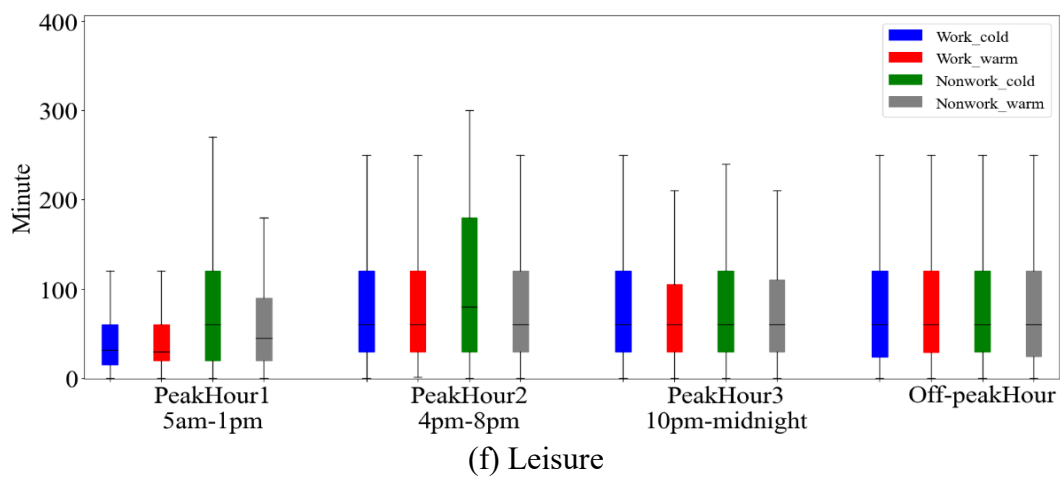
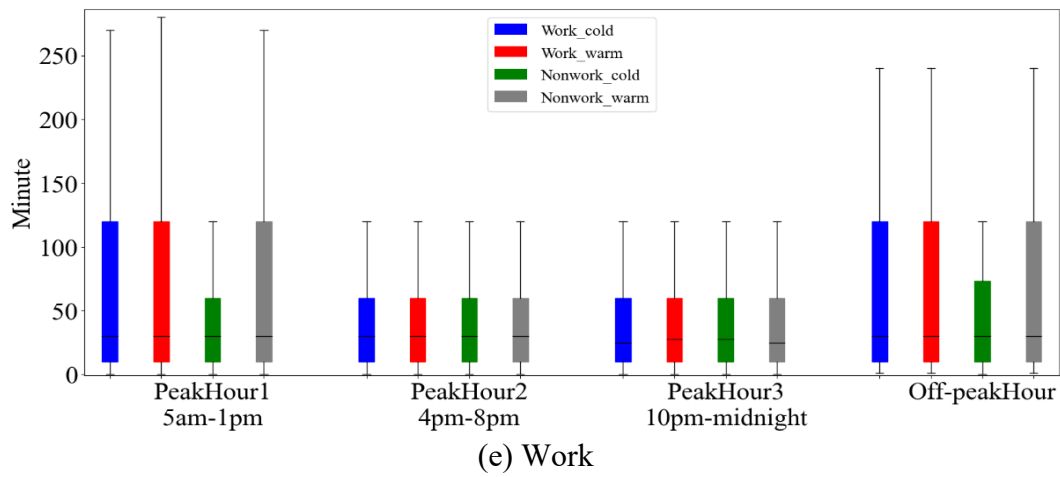


Figure 7.9 Duration of activities in peak and off-peak hours

7.2.2.4 Attitude

Participants' attitudes toward six sets of statements are summarised in Figure 7.10. Findings include:

Statements (1) and (2): More than 60% of participants are aware of the importance of energy conservation and the impact of their behaviours on the environment and society, and especially their electricity bills.

Statement (3): The impact on electricity bills plays a vital role in activity scheduling for 73.73% of participants. Furthermore, one-third of participants will also seriously consider the environmental and social impact.

Statements (4)-(6): About half of the participants hold positive attitudes toward ToU tariffs. The large gap between this relatively high preference and the low real penetration rate in Section 7.2.2.2 needs to be studied to promote ToU tariffs.

Energy Demand Modelling and Demand-Side Management with Detailed Representation of Consumer Activities and Behaviours

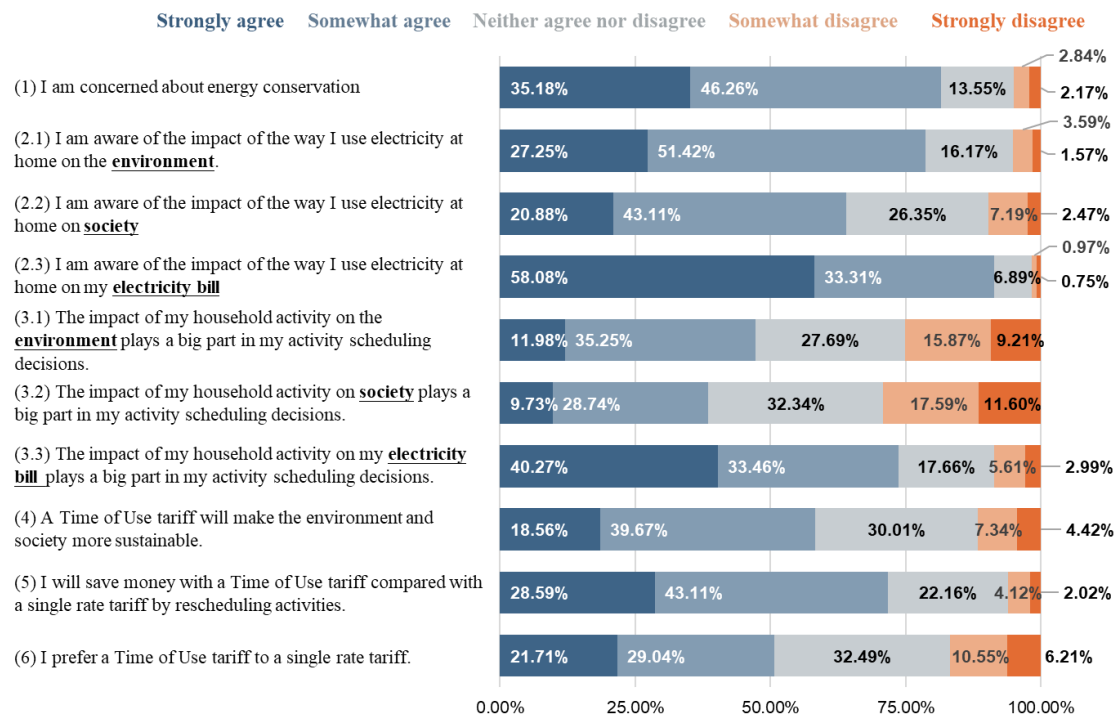


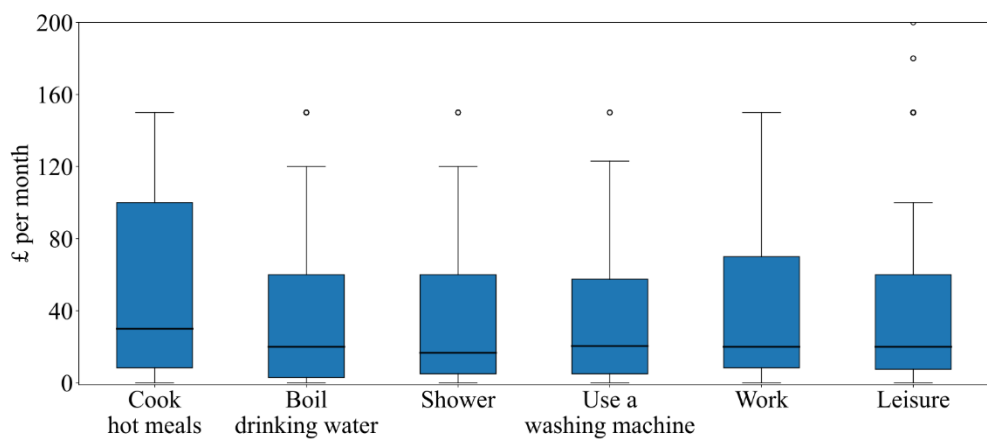
Figure 7.10 Attitude statement

7.2.2.5 Bias and value boundary

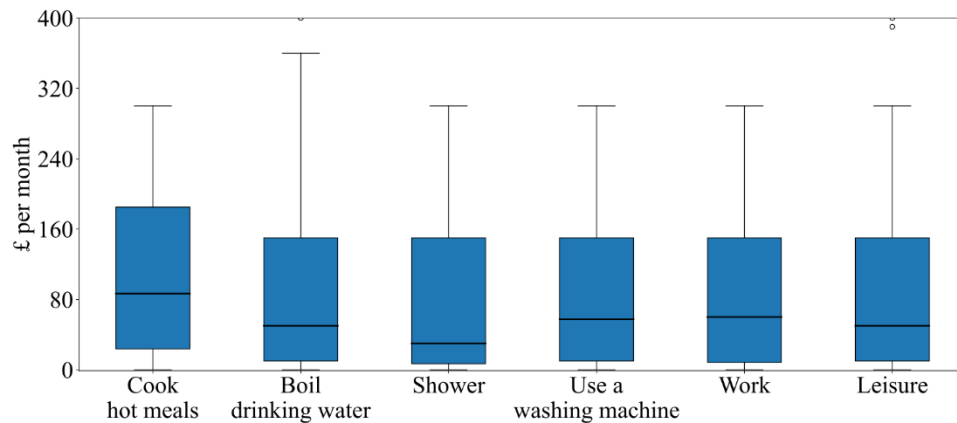
Many kinds of biases may exist in the SP survey such as the disregard of specific alternatives or attributes. In the DSM-SP survey, less than 7% of participants admitted to ignoring specific attributes or alternatives when answering the SP questions in hypothetical situations. While 1333 participants were recruited in the DSM-SP survey, about 2317 sets of choice situations were recorded because a large number of participants reported different choices in the default context plus another context. Each set of choice situations contains six hypothetical choice situations and about 14.02% of these sets exclusively obtained the choice of Alternative C “No change”. Similarly the percentages of sets with only the choice of Alternative A “Reschedule” or Alternative B “Reduce/Drop” are 3.80% and 8.46% respectively. These figures also suggest that very few participants ignore specific alternatives or attributes.

What is more, participants were asked about the value boundary of daily, monthly or yearly payments or savings above which they will consider adapting activities, i.e., considering Alternative A “Reschedule” or B “Reduce/Drop”. However, only about 60 to 80 participants responded to this question, which is not surprising as the calculation of value in different units can be challenging. Despite the fewer responses, these value boundaries are shown in Figure 7.11.

Figure 7.11 shows that “Cook hot meals” is the most inflexible activity among the six common activities. Half of the participants may consider adapting “Cook hot meals” when the saving of activity adaptation is beyond the median of about 30.00 £ per month or the payment of undertaking the activity during original peak hours is beyond the median of about 86.67 £ per month. On the other hand, “Shower” is the most flexible activity among the six activities, with a median saving boundary of 16.67 £ per month and a median payment boundary of 30.00 £ per month. The boundaries obtained from a larger sample size can be used to estimate the percentage of participants who will adapt activity schedules based on the impacts of ToU tariffs on savings and payments.



(a) The saving boundary beyond which the activity adaptation is considered



(b) The payment boundary beyond which the activity adaptation is considered

Figure 7.11 Value boundary of activity adaptation

7.3 Choice models and analysis of results

Data collected from the DSM-SP survey was used to build Multinomial logit (MNL) models and mixed logit models, as introduced in Section 2.4.4, to study the adaptation of activities. The data from each block of stated choice experiments, corresponding to

one activity type and one type of value change (saving or payment), was first processed to remove variables with minimal representation. Subsequently, an MNL model was estimated based on the processed data and the model specification was improved by removing variables exhibiting multicollinearity. Lastly, the remaining variables in MNL models are used to estimate a mixed logit model. The details and results of this specification search are provided in the next section. As a result, a “WTA” model and a “Threshold” model, named after their respective types of value measurements, are estimated for each type of activity, leading to a total of twelve mixed logit models.

7.3.1 Model structure

The initial utility functions include the variables related to alternatives, contexts, and socio-demographics. For one activity with one measuring way of value change, the utility functions are presented in Equations (7.4)-(7.6)

$$U_A = ASC_A + \beta_{OffPeakHour1} \cdot T_{OffPeakHour1} + \beta_{OffPeakHour2} \cdot T_{OffPeakHour2} + \beta_{value} \cdot VC_A + \beta_{context-A} \cdot X_{context} + \beta_{S-A} \cdot S + \eta_A + \varepsilon_A \quad (7.4)$$

$$U_B = ASC_B + \beta_{value} \cdot VC_B + \beta_{New} \cdot E_{new} + \beta_{context-A} \cdot X_{context} + \beta_{S-B} \cdot S + \eta_B + \varepsilon_B \quad (7.5)$$

$$U_C = \beta_{value} \cdot VC_C + \varepsilon_C \quad (7.6)$$

where several variables and parameters are the same as those in the SCE design, such as the alternative specific constant ASC , consumer sensitivity β , dummy variable of rescheduled time of activity $T_{OffPeakHour1}$ and $T_{OffPeakHour2}$. VC is the value change of alternatives, such as the saving in “WTA” and payment in “Threshold”. $X_{context}$ are the context-related variables, including seasons, working or non-working days, and the original activity time. S represents the socio-demographic variables of the respondents. E_{new} is the electricity consumption ratio in Alternative B “Reduce/Drop”. In the mixed logit models, the panel effects are considered to capture correlations across multiple responses from the same individual. Consequently, normally distributed errors η_A and η_B are added to the utilities of Alternatives A “Reschedule” and B “Reduce/Drop” respectively. ε is the error term.

Several variables from the DSM-SP survey were removed from the utility functions for the following reasons. Firstly, some variables have issues of collinearity with value

change, such as peak prices and off-peak prices. Additionally, consistent with the findings of the exploratory analysis, several socio-demographic variables in the blocks of specific activity are underrepresented. For example, most participants live in England and few participants own electric vehicles. Further, MNL models were used to improve the model specification before estimating the mixed logit models. Some variables that are expected to have an influence based on daily experience were statistically insignificant, such as living with children or older people, and the knowledge of current energy prices. In summary, underrepresented variables, variables with collinearity issues and variables that are removed in MNL models to improve model specification were omitted. After the specification search, variables in the initial utility function of the mixed logit model are listed in Table 7.6. Since some explanatory variables in the model are not specific to the alternatives, the coefficients of these variables are specified to be alternative-specific. All models and parameters are estimated using Python Biogeme (Bierlaire, 2020) and the results are shown in the next section.

Table 7.6 Variables in the utility functions

Group	Name	Description, value and data type
Alternative specific constant	Alternative specific constant	-
Alternative and context	Original time	Morning peak 05:00-13:00
		Afternoon peak 16:00-20:00
		Night peak 22:00-24:00 (fixed)
		Description: Time periods when the activity is originally undertaken. It is randomly selected based on the reported real-world schedule in the DSM-SP survey
	Electricity consumption ratio	Description: The ratio of the new electricity consumption to the original electricity consumption. Continuous variable
	Non-working day	Dummy variable
	Rescheduled time	Off-peak 1, 00:00 -05:00 (fixed)
		Off-peak 2, 13:00 - 16:00
		Off-peak 3, 20:00 - 22:00
	Saving/Payment	Continuous variable
	Warm season	Dummy variable
Socio-demographics	Age range	< 34 years old (fixed)
		35-44 years old
		45-54 years old

		55-64 years old
		65+ years old
	Annual household income less than £40,000	Dummy variable
	Employment status	Other (fixed)
		Working full-time
		Working part-time
	Female	Dummy variable
	No. of adults living with	0
		1
		2 or more (fixed)
	Live in a rented property	Dummy variable
	Live in a detached house, cottage or bungalow	Dummy variable
	Smart meter	Description: Equipment ownership. Dummy variable
	ToU tariff	Description: Participants' tariffs in the real world. Dummy variable
Panel effect	Panel effect	-

7.3.2 Results

In the following subsections, the results of the estimated mixed logit models are presented and discussed based on the activity type. Notably, while the coefficients from the “WTA” model and the “Threshold” model for each activity type are displayed in the same table, these values cannot be compared directly. These two models are listed together to highlight the significance of the variables. Segmented variables failing the Likelihood Ratio (LR) tests in each model were combined. Therefore, some variables are presented exclusively in one type of model and then marked as “N/A” in another model. In the final Subsection 7.3.2.7, variables and their coefficients are analysed across activities. One of the main common findings is that participants are sensitive to the payments they are charged but not to the savings. In addition, the negative coefficient related to payments across all “Threshold” models suggests that as the payment charged to consumers for an alternative increases, the likelihood of choosing the alternative decreases.

7.3.2.1 Cook hot meals

Table 7.7 shows the estimated models for the activity “Cook hot meals”. For “Cook hot meals”, the “Threshold” model seems like a more effective model with more statistically significant parameters. These coefficients show that:

- (1) Alternative specific constants are insignificant in the “WTA” model. However, they are significantly negative (coefficient: -4.59 and -5.82) in the “Threshold” model indicating that participants prefer Alternative C “No change” all else being equal.
- (2) Alternative and context attributes: Two original peak hours, i.e., 05:00-13:00 and 16:00-20:00 show similar contributions (coefficient: 1.91) to the choice of activity adaptation in the “Threshold” model. On non-working days, participants are more inclined to reschedule activity start time in the “WTA” model (coefficient: 1.02) and reduce activity intensity in the “Threshold” model (coefficient: 0.56). This indicates that “Cook hot meals” are more flexible on non-working days compared with working days, which complies with common sense. However, the explanation of the different preferences for alternatives on non-working days in the “WTA” and “Threshold” models is challenging due to the limited set of variables studied. As expected, when the activity is rescheduled, off-peak in the afternoon (13:00-16:00) is preferred (coefficient: 0.65) to very early or very late off-peak hours in the “WTA” model. On the other hand, in the “Threshold” model, the difference between the preference for afternoon (13:00-16:00) and night (20:00-22:00) off-peak hours is insignificant (coefficient: 0.881). In addition, the warm season (coefficient: 1.13) increases the probability of adapting the activity patterns.
- (3) Socio-demographic attributes: Older age (>55 years old, coefficient: 2.4), currently working (coefficient: 1.9), not living alone (coefficient of living alone: -1.38), living in rented property (coefficient: 1.81) and ownership of smart meters (coefficient: 2.46) increase the probability of adapting activity patterns in the “Threshold” model.
- (4) Panel effects are significant in both models.

Table 7.7 Estimation of “Cook hot meals”

Attribute-specific to alternatives (A.Reschedule; B. Reduce/Drop)	WTA		Threshold	
	Value	p-value	Value	p-value

Alternative specific constant		Reschedule	0.144	0.92	-4.59	***
		Reduce/Drop	0.305	0.813	-5.82	***
Alternative and context						
Original time	05:00-13:00	Reduce/Drop			1.91	**
	16:00-20:00	Reduce/Drop				
	22:00-24:00		0	(fixed)	0	(fixed)
Non-working day		Reschedule	1.02	***		
		Reduce/Drop			0.56	**
Rescheduled time	00:00-05:00		0	(fixed)	0	(fixed)
	13:00-16:00	Reschedule	0.65	***	0.881	***
	20:00-22:00	Reschedule	0.287	0.267		
Saving/Payment			0.105	0.157	-0.215	***
Warm season		Reschedule; Reduce/Drop			1.13	***
Socio-demographics						
Age range	< 34		0	(fixed)	0	(fixed)
	55+	Reschedule; Reduce/Drop			2.4	***
Employment status	Other		0	(fixed)	0	(fixed)
	Working (full/part-time)	Reschedule; Reduce/Drop			1.9	***
No. of adults living with	0	Reschedule			-1.38	**
	2 or more		0	(fixed)	0	(fixed)
Property ownership	Rented	Reschedule; Reduce/Drop			1.81	***
Smart meter		Reschedule; Reduce/Drop			2.46	***
Panel effect						
Error term		Reschedule	1.26	***	0.844	***
		Reduce/Drop	1.36	***	1.37	***
Model fit statistics						
Initial log-likelihood			-1029.578		-1015.122	
Final log-likelihood			-970.6865		-864.032	
AIC			2029.373		1794.064	
BIC			2148.194		1883.774	
Adjusted Rho2			0.0145		0.116	

** : $p < 0.05$

*** : $p < 0.01$

7.3.2.2 Boil drinking water

Table 7.8 shows the estimated models for the activity “Boil drinking water”. These coefficients show that:

- (1) Alternative specific constants are insignificant in both models.
- (2) Alternative and context attributes: In the “Threshold” model, participants are less inclined to reschedule “Boil drinking water” during the morning peak 05:00-13:00 (coefficient: -2.14) compared with the nighttime. On the contrary, a non-working day increases the probability for consumers to reduce/drop the electricity intensity of the activity (coefficient: 0.73). Additionally, if rescheduled, participants prefer to reschedule this activity to the afternoon (13:00-16:00, coefficient: 0.536) in comparison to other off-peak hours. The warm season increases the probability of adapting activity patterns in both models (coefficients: 1.7 and 1.13).
- (3) Socio-demographic attributes: In the “WTA” model, older participants (>55 years old) are less likely to change the pattern of “Boil drinking water” (coefficient: -4.73). On the contrary, participants with full-time jobs are more likely to reduce the activity intensity (coefficient: 1.71). Additionally, living alone increases the likelihood of changing the activity (coefficient: 2.22). In the “Threshold” model, middle-aged participants (35-44 years old, coefficient: 1.59) and participants with smart meters (coefficient: 1.4) are inclined to reduce electricity intensity.
- (4) Panel effects are significant in both models.

Table 7.8 Estimation of “Boil drinking water”

Attribute-specific to alternatives (A. Reschedule; B. Reduce/Drop)			WTA		Threshold	
			Value	p-value	Value	p-value
Alternative specific constant	Reschedule		-0.321	0.802	-1.75	0.316
	Reduce/Drop		0.244	0.845	-2.78	0.11
Alternative and context						
Original time	05:00-13:00	Reschedule			-2.14	***
	22:00-24:00		0	(fixed)	0	(fixed)
Non-working day		Reduce/Drop			0.73	**
Rescheduled time	00:00-05:00		0	(fixed)	0	(fixed)
	13:00-16:00	Reschedule	0.418	0.104	0.536	**
	20:00-22:00	Reschedule	0.282	0.295	-0.232	0.418
Saving/Payment			0.171	0.086	-0.553	***
Warm season		Reschedule; Reduce/Drop	1.7	***	1.13	***
Socio-demographics						
Age range	< 34		0	(fixed)	0	(fixed)
	35-44	Reduce/Drop			1.59	**

	55+	Reschedule; Reduce/Drop	-4.73	***		
Employment status	Working full-time	Reduce/Drop	1.71	**		
Annual household income	< £40,000	Reduce/Drop	1.21	**		
No. of adults living with	0	Reschedule; Reduce/Drop	2.22	***		
	2 or more		0	(fixed)	0	(fixed)
Smart meter		Reduce/Drop			1.4	**
Panel effect						
Error term		Reschedule	1.94	***	1.39	***
		Reduce/Drop	1.5	***	-1.51	***
Model fit statistics						
Initial log-likelihood			-929.8401		-938.985	
Final log-likelihood			-805.1417		-804.3287	
AIC			1688.283		1694.657	
BIC			1794.305		1810.385	
Adjusted Rho2			0.0922		0.0976	

** : $p < 0.05$

*** : $p < 0.01$

7.3.2.3 Shower

Table 7.9 shows the estimated models for the activity “Shower”. These coefficients show that:

- (1) Alternative specific constants are insignificant in the “Threshold” model and indicate a lower preference (coefficient: -3) for rescheduling activity in the “WTA” model all else being equal.
- (2) Alternative and context attributes: Participants tend to reschedule the activity on non-working days in the “Threshold” model (coefficient: 0.722). In both models, if rescheduled, participants prefer to reschedule this activity to the evening (20:00-22:00) compared with other hours (coefficients: 1.41 in the “WTA” model and 0.518 in the “Threshold” model).
- (3) Socio-demographic attributes: In the “Threshold” model, older participants (>45 years old) are less inclined to adapt the activity (coefficient: -1.3) while participants with lower incomes prefer activity adaptation (coefficient: 1.21). In the “WTA” model, having a ToU tariff (coefficient: 1.45) and living in

relatively expensive properties (coefficient:1.3) increase the likelihood of adapting the activity.

(4) Panel effects are significant in both models.

Table 7.9 Estimation of “Shower”

Attribute-specific to alternatives (A.Reschedule; B. Reduce/Drop)			WTA		Threshold	
			Value	p-value	Value	p-value
Alternative specific constant	Reschedule		-3	**	0.232	0.851
	Reduce/Drop		-1.3	0.425	0.908	0.505
Alternative and context						
Non-working day		Reschedule			0.722	**
Rescheduled time	00:00-05:00		0	(fixed)	0	(fixed)
	13:00-16:00	Reschedule	0.823	***	0.373	0.0858
	20:00-22:00	Reschedule	1.41	***	0.518	**
Saving/Payment			-0.0104	0.83	-0.167	***
Socio-demographics						
Age range	< 34		0	(fixed)	0	(fixed)
	45+	Reschedule; Reduce/Drop			-1.3	**
Annual household income	< £40,000	Reschedule; Reduce/Drop			1.21	**
Property type	Detached house, cottage or bungalow	Reduce/Drop	1.3	**		
ToU tariff		Reschedule	1.45	**		
Panel effect						
Error term	Reschedule		1.53	***	1.01	***
	Reduce/Drop		2.1	***	1.61	***
Model fit statistics						
Initial log-likelihood			-1030.124		-1017.12	
Final log-likelihood			-953.6174		-941.5385	
AIC			1995.235		1959.077	
BIC			2116.012		2061.695	
Adjusted Rho2			0.0316		0.0369	

** : p<0.05

***: p<0.01

7.3.2.4 Use a washing machine

Table 7.10 shows the estimated models for the activity “Use a washing machine”. These coefficients show that:

- (1) Alternative specific constants are insignificant in “Threshold” models and show a lower probability of rescheduling activity in the “WTA” model (coefficient: -2.46) all else being equal.
- (2) Alternative and context attributes: This activity is more flexible during the earlier peak hours (05:00-13:00 and 16:00-20:00, coefficient:1.76) compared to the late-night peak hours (22:00-24:00), and is preferred to be scheduled to later off-peak hours (13:00-16:00 and 20:00-22:00, coefficients: 0.72 and 0.668) if rescheduled, compared to off-peak hours after midnight (00:00-05:00).
- (3) Socio-demographic attributes: In the “WTA” model, older participants (35-64 years old, coefficient: 1.86) are more likely to reschedule the activity while people living alone (coefficients: -1.26) are less likely to reschedule the activity. In the “Threshold” model, middle-aged participants (35-44 years old, coefficient: -1.83) dislike the rescheduling of the activity. Conversely, having a ToU tariff increases the possibility of adapting the activity patterns (coefficient: 2.37).
- (4) Panel effects are significant in both models.

Table 7.10 Estimation of “Use a washing machine”

Attribute-specific to alternatives (A.Reschedule; B. Reduce/Drop)			WTA		Threshold	
			Value	p-value	Value	p-value
Alternative specific constant	Reschedule		-2.46	**	0.841	0.545
	Reduce/Drop		-1.47	0.258	-0.657	0.742
Alternative and context						
Original time	05:00-13:00	Reschedule;				
	16:00-20:00	Reduce/Drop	1.76	***		
	22:00-24:00		0	(fixed)	0	(fixed)
Rescheduled time	00:00-05:00		0	(fixed)	0	(fixed)
	13:00-16:00 20:00-22:00	Reschedule	0.72	***	0.668	***
Saving/Payment			0.0699	0.403	-0.573	***
Socio-demographics						
Age range	< 34		0	(fixed)	0	(fixed)
	35-44	Reschedule			-1.83	**
	45-54	Reschedule				
	55-54	Reschedule	1.86	***		
No. of adults living with	0	Reschedule	-1.26	**		
	2 or more		0	(fixed)	0	(fixed)
ToU tariff		Reschedule; Reduce/Drop			2.37	**

Panel effect					
Error term	Reschedule	1.07	***	1.55	***
	Reduce/Drop	1.37	***	2.04	***
Model fit statistics					
Initial log-likelihood		-970.5976		-949.6646	
Final log-likelihood		-893.842		-788.4689	
AIC		1863.684		1660.938	
BIC		1965.605		1775.115	
Adjusted Rho2		0.0399		0.126	

** : $p < 0.05$

*** : $p < 0.01$

7.3.2.5 Leisure

Table 7.11 shows the estimated models for the activity “Leisure”. These coefficients show that:

- (1) Alternative specific constants show that rescheduling this activity is not preferred in the “WTA” model all else being equal (coefficient: -3.59).
- (2) Alternative and context attributes: In the activity adaptation in the “WTA” model, participants are inclined to reschedule this activity from the morning peak (05:00-13:00, coefficient: 1.83) to the off-peak hours in the afternoon and night (13:00-16:00 and 20:00-22:00, coefficient: 0.542) compared with the other hours. In the “Threshold” model, the warm season increases the probability of adapting the activity patterns (coefficients: 0.764 and 1.21).
- (3) Socio-demographic attributes: Older participants (55-64 years old) are more likely to change the activity patterns in the “WTA” model (coefficient: 3.1);
- (4) Panel effects are significant in both models.

Table 7.11 Estimation of “Leisure”

Attribute-specific to alternatives (A. Reschedule; B. Reduce/Drop)			WTA		Threshold	
			Value	p-value	Value	p-value
Alternative specific constant	Reschedule		-3.59	**	-2.55	0.0859
	Reduce/Drop		-2.73	0.0756	-2.55	0.0858
Alternative and context						
Original time	05:00-13:00	Reschedule	1.83	**		
	22:00-24:00		0	(fixed)	0	(fixed)
Rescheduled time	00:00-05:00		0	(fixed)	0	(fixed)
	13:00-16:00	Reschedule			0.146	0.466
	20:00-22:00	Reschedule	0.542	***	0.39	0.08
Saving/Payment			0.0976	0.0904	-0.236	***

Warm season		Reschedule			0.764	**
		Reduce/Drop			1.21	***
Socio-demographics						
Age range	< 34		0	(fixed)	0	(fixed)
	55-64	Reschedule; Reduce/Drop	3.1	***		
Panel effect						
Error term		Reschedule	1.44	**	1.29	**
		Reduce/Drop	1.82	***	1.55	***
Model fit statistics						
Initial log-likelihood			-972.5339		-1022.141	
Final log-likelihood			-905.9924		-926.9068	
AIC			1895.985		1941.814	
BIC			2010.535		2061.819	
Adjusted Rho2			0.0252		0.0501	

** : $p < 0.05$

*** : $p < 0.01$

7.3.2.6 Work

Table 7.12 shows the estimated models for the activity “Work”. These coefficients show that:

- (1) Alternative specific constants show that rescheduling this activity is not preferred in the “Threshold” model all else being equal (coefficient: -3.08).
- (2) Alternative and context attributes: In the “WTA” model, participants are less likely to adapt this activity during the daytime (05:00-13:00 and 16:00-20:00, coefficient: -2.06). In the “Threshold” model, non-working days (coefficient: 1.47) increase the likelihood of adapting the activity patterns and participants prefer to reschedule this activity to the off-peak hours (13:00-16:00, coefficient: 0.813) in the daytime if rescheduled.
- (3) Socio-demographic attributes: In the “WTA” model, female (coefficient: 1.7) is more likely to adapt activity patterns and living with fewer than two adults (coefficients: -2.17 and -1.85) reduces the possibility of adapting activity patterns. Having a ToU tariff increases the likelihood of reducing the electricity intensity in both models (coefficients: 2.73 and 2.21).
- (4) Panel effects are significant in both models.

Table 7.12 Estimation of “Work”

Attribute-specific to alternatives	WTA	Threshold
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(A.Reschedule; B. Reduce/Drop)			Value	p-value	Value	p-value
Alternative specific constant	Reschedule		-0.28	0.818	-3.08	**
	Reduce/Drop		-0.838	0.523	-2.93	0.0739
Alternative and context						
Original time	05:00-13:00	Reschedule	-2.06	***		
	16:00-20:00	Reschedule				
	22:00-24:00 (fixed)		0	(fixed)	0	(fixed)
Non-working day		Reschedule; Reduce/Drop			1.47	***
Rescheduled time	00:00-05:00		0	(fixed)	0	(fixed)
	13:00-16:00	Reschedule	0.83	***	0.813	***
	20:00-22:00	Reschedule			0.177	0.38
Saving/Payment			0.108	0.316	-0.616	***
Socio-demographics						
Age range	<34		0	(fixed)	0	(fixed)
	45-54	Reschedule	-1.96	**		
Female		Reschedule; Reduce/Drop	1.7	***		
No. of adults living with	0-1	Reschedule	-2.17	***		
	0	Reduce/Drop	-1.85	**		
	2 or more		0	(fixed)	0	(fixed)
ToU tariff		Reduce/Drop	2.73	***	2.21	**
Panel effect						
Error term	Reschedule		1.76	***	1.55	***
	Reduce/Drop		2.15	***	1.83	***
Model fit statistics						
Initial log-likelihood			-948.0938		-1013.664	
Final log-likelihood			-868.4657		-879.0309	
AIC			1816.931		1844.062	
BIC			1924.951		1959.79	
Adjusted Rho2			0.0418		0.0904	

** : $p < 0.05$

*** : $p < 0.01$

7.3.2.7 Summary

Table 7.13 shows all significant variables of all models. The impacts of variables across activities disregarding the difference between “WTA” and “Threshold” models are summarised below.

Alternative specific constants either are not significant or show that participants prefer not to adapt the patterns of activities all else being equal. The error component due to panel effects is significant for all models, indicating there is a substantial amount of

unobserved preference heterogeneity. The sources of this unobserved preference heterogeneity may be the relatively small sample size, the complexity of adapting activities, unintegrated attitudes and the absence of participants' overall activity schedules. Therefore, future work can utilise latent variables to include attitudes in the model and design new attributes for the overall daily schedule.

Activity time: The activity timing before and after rescheduling plays an important role in the choice. The original time influences the probability of adapting all activities except for "Shower". Compared with night peak hours (22:00-24:00), "Boil drinking water" and "Work" in the daytime peak hours (05:00-13:00 and 16:00-20:00) are less likely to be rescheduled. On the contrary, other influenced activities are more flexible in the daytime peak hours. As for the rescheduled time, as expected none of the participants exhibited a preference for the time after midnight (00:00-05:00). "Shower" is the only activity more preferred to be rescheduled to the night (20:00-22:00). "Use a washing machine" and "Leisure" show a similar preference to be rescheduled to the off-peak hours in the afternoon and night while other activities are preferably rescheduled to the afternoon off-peak hours (13:00-16:00).

Context variables: In all choice models of activities, participants are sensitive to the payments they are charged for undertaking activities in the way described in alternatives but not to the savings. Section 7.4.1 will discuss consumers' sensitivities to different ways of measuring value change, which has been studied in the economics and psychology literature. The warm season increases the probability of adapting the patterns of activities "Cook hot meals", "Boil drinking water" and "Leisure". The non-working days increase the probability of adapting the patterns of "Cook hot meals", "Boil drinking water", "Shower" and "Work".

Socio-demographic variables: Generally, socio-demographic variables have less impact on the choice models in this study due to the limited sample size per block. Based on the statistical results, older people prefer to adapt activities "Cook hot meals", "Use a washing machine" and "Leisure" while not to adapt the activities "Boil drinking water" and "Shower". Living with other adults reduces the possibility of rescheduling "Boil drinking water" but increases the possibility of changing "Cook hot meals" and "Work". As anticipated, having smart meters and ToU tariffs increases the probability of changing the patterns of almost all activities.

Table 7.13 Summary of estimations

Attribute-specific to alternatives (A.Reschedule; B. Reduce/Drop)			Cook hot meals		Boil drinking water		Shower		Use a washing machine		Leisure		Work	
W: WTA; T: Threshold			W	T	W	T	W	T	W	T	W	T	W	T
Alternative specific constant		Reschedule		-4.59			-3		-2.46		-3.59			-3.08
		Reduce/Drop		-5.82										
Alternative and context														
Original time	05:00-13:00	Reschedule				-2.14			1.76		1.83		-2.06	
		Reduce/Drop		1.91										
	16:00-20:00	Reschedule											-2.06	
		Reduce/Drop		1.91										
	22:00-24:00			0	0	0	0	0	0	0	0	0	0	0
Non-working day		Reschedule	1.02					0.722						1.47
		Reduce/Drop		0.56		0.73								
Rescheduled time	00:00-05:00		0	0	0	0	0	0	0	0	0	0	0	0
	13:00-16:00	Reschedule	0.65	0.881		0.536	0.823		0.72	0.668	0.542		0.83	0.813
	20:00-22:00	Reschedule				1.41	0.518							
Saving/Payment				-0.215		-0.553		-0.167		-0.573		-0.236		-0.616
Warm season		Reschedule		1.13	1.7	1.13						0.764		
		Reduce/Drop										1.21		
Socio-demographics														
Age range	< 34		0	0	0	0	0	0	0	0	0	0	0	0
	35-44	Reschedule							1.86	-1.83				
		Reduce/Drop				1.59								
	45-54	Reschedule						-1.3					-1.96	
	55-64	Reschedule		2.4							3.1			

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		Reduce/Drop			-									
	65+	Reschedule; Reduce/Drop			4.73									
Annual household income	< £40,000	Reschedule; Reduce/Drop						1.21						
Employment status	Other		0	0	0	0	0	0	0	0	0	0	0	0
	Working full-time	Reschedule		1.9										
		Reduce/Drop			1.71									
	Working part-time	Reschedule												
		Reduce/Drop												
Female		Reschedule; Reduce/Drop											1.7	
No. of adults living with	0	Reschedule		-1.38	2.22				-1.26				-2.17	
		Reduce/Drop											-1.85	
	1	Reschedule											-2.17	
	2 or more		0	0	0	0	0	0	0	0	0	0	0	0
Property ownership	Rented	Reschedule; Reduce/Drop		1.81										
Property type: Detached house, cottage or bungalow		Reduce/Drop					1.3							
Smart meter		Reschedule		2.46										
		Reduce/Drop			1.4									
ToU tariff		Reschedule					1.45			2.37				
		Reduce/Drop										2.73	2.21	
Panel effect		Reschedule	1.26	0.844	1.94	1.39	1.53	1.01	1.07	1.55	1.44	1.29	1.76	1.55
		Reduce/Drop	1.36	1.37	1.5	-1.51	2.1	1.61	1.37	2.04	1.82	1.55	2.15	1.83

7.4 Case study and application

The choice models estimated in this chapter can be used to predict consumer responses to electricity tariffs and the consequential cost savings in DSM. In addition, the design of ToU tariffs and energy policies can take advantage of the results to assess the impacts of price levels on demand shifting and electricity bill savings. To show the aforementioned application of these models, a case study is designed.

This case study aims to predict consumers' choices between rescheduling activities (Alternative A), reducing the electricity intensity of activities (Alternative B) and no change (Alternative C) during peak hours when they switch to ToU tariffs. The scope of this case study is limited to the afternoon peak (16:00-20:00) as it typically represents the highest peak demand during the day. In Alternative A "Reschedule", activities are rescheduled to the preferred off-peak period, as identified by the estimated mixed logit choice model. For example, "Cook hot meals", "Boil drinking water", "Use a washing machine" and "Work" are rescheduled to 13:00-16:00. On the contrary, "Shower" and "Leisure" are rescheduled to 20:00-22:00. In Alternative B "Reduce/Drop", the electricity intensity of the activity is reduced to 50% for simplicity. The context is set as working days in the cold season and the socio-demographics of 1333 participants is drawn from the DSM-SP survey. Moreover, the choice to adapt activities applies only to participants who reported undertaking the activity during the afternoon peak in the DSM-SP survey.

Several scenarios of peak and off-peak prices in ToU tariffs are designed based on the reported tariffs in the DSM-SP survey, as shown in Table 7.14. Since the main levels of ToU prices reported in the DSM-SP survey are beyond 0.4 £/kWh in peak hours and below 0.2 £/kWh in off-peak hours, the default Scenario 1 sets the borderlines as these price values. Then Scenarios 2, 3 and 4 are designed to respectively reduce the off-peak price, raise the peak price and raise both prices at the same time while maintaining the gap between peak and off-peak prices.

Table 7.14 Price scenarios

	Peak price (£/kWh)	Off-peak price (£/kWh)	Compared with Scenario 1
Scenario 1	0.40	0.20	-
Scenario 2	0.40	0.10	Reduce off-peak price
Scenario 3	0.50	0.20	Increase peak price

Scenario 4	0.50	0.30	Increase both but maintain the gap
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7.4.1 Results

Firstly, the estimated choice models are used to predict the selection share of each alternative for each activity in the population sample with a 95% confidence interval (Bierlaire, 2018). Secondly, the impact of these choices on aggregated load profiles and overall electricity bills is calculated based on the selection share, the average electricity consumption of activities (as shown in Table 7.2) and the electricity prices. Lastly, the impacts are averaged to the household level for analysis. The results are shown in Table 7.15. It is important to note that the distribution of selection shares is not well-defined and is unlikely to be a standard normal distribution, as evidenced by the asymmetrical confidence intervals around the mean. Consequently, the confidence intervals of the aggregated load shifting, as well as the savings and payments in electricity bills cannot be estimated based on the confidence interval of selection shares.

Table 7.15 Prediction results

Alternative selection share				
- Cook hot meals (size: 1105)				
Alternative	Scenario 1	Scenario 2	Scenario 3	Scenario 4
A. Reschedule	30.67% [16.34%, 47.02%]	34.30% [18.69%, 51.79%]	32.27% [17.53%, 49.38%]	28.74% [15.33%, 44.08%]
B. Reduce/Drop	33.52% [20.06%, 49.21%]	31.58% [18.03%, 47.34%]	35.04% [20.67%, 50.13%]	37.05% [22.61%, 52.69%]
C. No change	35.81% [20.50%, 52.81%]	34.12% [18.74%, 51.10%]	32.69% [18.68%, 49.67%]	34.21% [19.32%, 51.17%]
- Boil drinking water (size: 870)				
Alternative	Scenario 1	Scenario 2	Scenario 3	Scenario 4
A. Reschedule	27.61% [10.52%, 47.99%]	43.10% [20.49%, 65.75%]	31.04% [12.89%, 52.03%]	18.30% [6.19%, 35.65%]
B. Reduce/Drop	55.50% [32.50%, 75.41%]	44.37% [23.75%, 63.86%]	60.20% [36.31%, 78.19%]	70.42% [45.26%, 85.64%]
C. No change	16.89% [4.45%, 40.67%]	12.52% [3.10%, 34.14%]	8.76% [1.85%, 27.59%]	11.28% [2.92%, 32.52%]
- Shower (size:507)				
Alternative	Scenario 1	Scenario 2	Scenario 3	Scenario 4
A. Reschedule	40.41% [23.02%, 55.65%]	47.48% [30.47%, 62.79%]	42.47% [25.35%, 58.07%]	35.65% [19.62%, 51.54%]
B. Reduce/Drop	43.53% [26.10%, 61.83%]	38.70% [22.63%, 53.69%]	45.21% [27.24%, 61.84%]	50.17% [31.06%, 67.83%]
C. No change	16.06% [5.88%, 35.42%]	13.83% [5.00%, 30.94%]	12.31% [4.20%, 29.61%]	14.18% [4.89%, 32.38%]

- Use a washing machine (size: 463)				
Alternative	Scenario 1	Scenario 2	Scenario 3	Scenario 4
A. Reschedule	69.12% [42.75%, 85.01%]	78.11% [55.07%, 90.65%]	72.53% [46.97%, 88.10%]	62.80% [37.33%, 81.18%]
B. Reduce/Drop	19.86% [6.99%, 42.91%]	14.57% [4.35%, 33.46%]	20.95% [7.09%, 44.68%]	27.54% [9.94%, 52.42%]
C. No change	11.02% [3.12%, 27.30%]	7.32% [1.79%, 20.83%]	6.52% [1.36%, 18.46%]	9.66% [2.56%, 24.58%]
- Leisure (size:878)				
Alternative	Scenario 1	Scenario 2	Scenario 3	Scenario 4
A. Reschedule	28.19% [13.64%, 47.23%]	35.64% [17.43%, 54.82%]	31.45% [15.57%, 49.38%]	24.51% [11.23%, 40.22%]
B. Reduce/Drop	40.36% [19.96%, 58.21%]	36.51% [17.97%, 53.24%]	44.15% [23.57%, 61.96%]	48.16% [26.17%, 66.29%]
C. No change	31.45% [10.85%, 59.07%]	27.85% [9.51%, 55.33%]	24.40% [7.70%, 50.65%]	27.33% [9.61%, 54.64%]
- Work (size: 671)				
Alternative	Scenario 1	Scenario 2	Scenario 3	Scenario 4
A. Reschedule	53.35% [29.15%, 73.11%]	63.16% [36.34%, 81.93%]	57.84% [31.81%, 77.08%]	47.99% [25.95%, 69.04%]
B. Reduce/Drop	25.41% [10.28%, 45.24%]	20.50% [7.73%, 39.77%]	27.56% [11.21%, 48.68%]	33.30% [14.79%, 54.50%]
C. No change	21.24% [7.00%, 44.97%]	16.34% [4.38%, 38.84%]	14.60% [3.95%, 36.90%]	18.71% [5.59%, 40.44%]
Energy profile reshaping (1000 kWh/month)				
Alternative	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Rescheduled in Alternative A	28.16	35.08	30.44	24.10
Reduced in Alternative B	15.40	13.24	16.51	18.69
Remain in Alternative C	18.03	15.43	13.53	15.51
Saving and payment (1000 £/month)				
Alternative	Scenario 1	Scenario 2	Scenario 3	Scenario 4
A. reschedule saving	5.63	10.52	9.13	4.82
B. Reduce saving	6.16	5.30	8.25	9.35
Aggregated saving	11.79	15.82	17.39	14.17
Aggregated post-adaptation payment	28.24	22.92	29.36	33.68
Household average (£/month or kWh/month)				
Reduced and rescheduled electricity	32.68	36.25	35.22	32.10

Saving	8.85	11.87	13.04	10.63
Post-adaptation payment	21.19	17.20	22.03	25.26

Figure 7.12 shows the monthly household savings and payments across the four price scenarios from the consumers' perspective. The results of Scenarios 2, 3 and 4 are compared to that of Scenario 1 to analyse the impact of the different pricing policies. As anticipated, Scenario 2 with a lower off-peak price encourages more participants to reschedule indoor activities to off-peak hours, leading to more reschedule savings. Higher peak prices in Scenario 3 stimulate more savings through both rescheduling activity start times and reducing electricity intensity. If both peak prices and off-peak prices increase as shown in Scenario 4, more participants tend to reduce the electricity intensity rather than reschedule activity start times since the difference between peak and off-peak prices does not change.

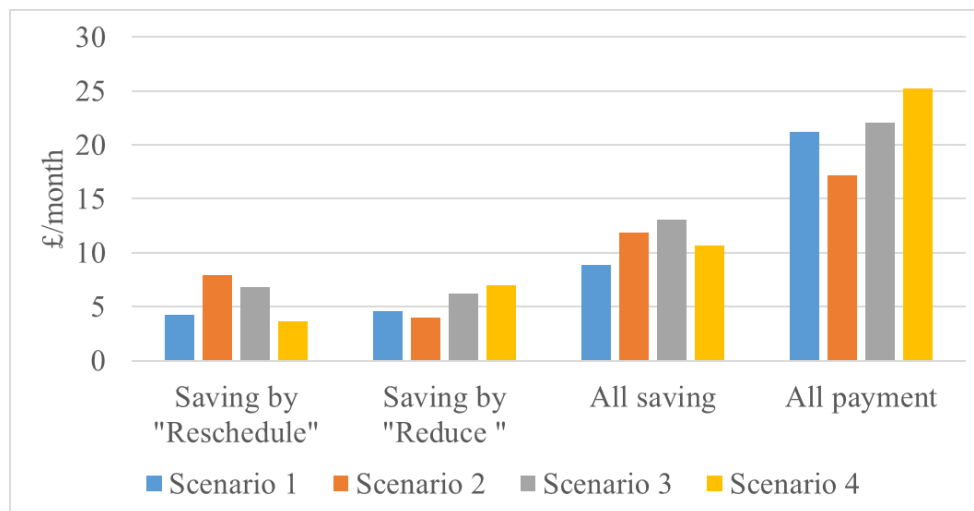


Figure 7.12 Household savings and post-adaptation payments across scenarios

From the perspective of electricity providers, consumers' behaviours of adapting activity patterns will reduce electricity payments but the electricity demand in the peak periods will reduce as well. Figure 7.13 shows that more than half of the household electricity demands in the afternoon peak hours driven by these six activities are either rescheduled or reduced. Therefore, this case study suggests that reducing peak load and reshaping load profiles can be effectively achieved through ToU tariffs. Electricity providers may choose to reduce the off-peak price to obtain more peak load reduction in Scenario 2 or raise both peak and off-peak prices to achieve a relatively high income in Scenario 4.

Notably, as stated in Section 7.3.2.7, estimated choice models in this chapter have a substantial amount of unobserved preference heterogeneity, leading to relatively large confidence intervals in the case study. Despite the uncertainty, the analysis shows that policymakers and electricity providers can utilise these choice models to quantitatively weigh the benefits and losses of different price scenarios.

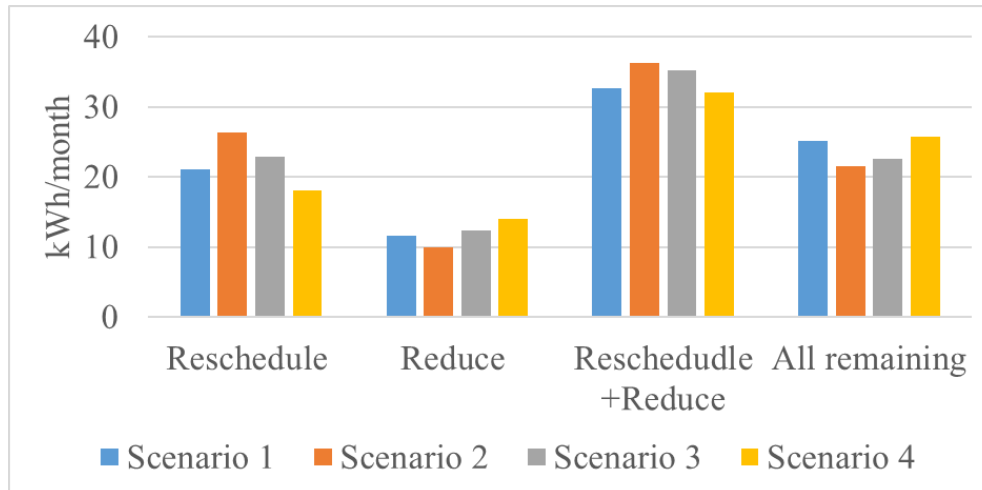


Figure 7.13 Change of household demand profiles in the afternoon peak hours

7.4.2 Distributional impacts

The distributional impacts of the ToU tariffs on households are analysed from three perspectives, i.e., annual income, presence of children and UK regions. These factors are selected since they are used to segment consumers in the literature (Yunusov & Torriti, 2021) and are available in the DSM-SP survey. In addition, households divided by these factors are expected to exhibit different activity schedules and lifestyles, which in turn affect their choices in activity adaptation. However, the impact of these individual factors is not reflected in estimated choice models, as indicated by their insignificant coefficients. Therefore, the distributional impacts across these factors are further examined. Households represented by participants are grouped based on one of these three features at a time and their averaged selection share across four scenarios of ToU tariffs are compared.

7.4.2.1 Annual income

Households in the DSM-SP survey are categorised into two income groups, i.e., 669 households with an annual income beyond £40000 and 664 households with an annual income below £40000. Given the unequal size of these two groups, the average share of the chosen alternatives, as well as household average savings and payments are

shown in Table 7.16 for comparison. The results show that households with higher income are less likely to change the patterns of essential activities “Cook hot meals” and “Shower” but are more flexible about the electricity intensity of activity “Leisure”. The percentage saving on the bottom row of the table, which is the saving divided by the sum of savings and post-adaptation payments, shows that households with lower income can save slightly more from ToU tariffs.

Table 7.16 Results of the two income groups

Alternative selection share		
- Cook hot meals		
Alternative	Lower-income group	Higher-income group
A. Reschedule	31.20% [16.96%, 47.74%]	28.91% [16.14%, 44.45%]
B. Reduce/Drop	40.10% [24.54%, 56.18%]	30.18% [17.37%, 45.09%]
C. No change	28.70% [15.20%, 45.27%]	40.91% [24.19%, 58.16%]
- Boil drinking water		
Alternative	Lower-income group	Higher-income group
A. Reschedule	29.86% [12.24%, 51.15%]	30.91% [13.49%, 50.01%]
B. Reduce/Drop	57.38% [33.40%, 75.92%]	57.31% [35.68%, 74.83%]
C. No change	12.76% [3.04%, 35.01%]	11.78% [3.05%, 31.47%]
- Shower		
Alternative	Lower-income group	Higher-income group
A. Reschedule	45.60% [26.73%, 61.75%]	37.88% [21.44%, 53.70%]
B. Reduce/Drop	44.89% [27.40%, 63.04%]	43.94% [26.43%, 61.37%]
C. No change	9.51% [2.91%, 24.61%]	18.18% [6.55%, 38.06%]
- Use a washing machine		
Alternative	Lower-income group	Higher-income group
A. Reschedule	70.78% [46.62%, 85.84%]	70.47% [46.49%, 85.92%]
B. Reduce/Drop	19.85% [6.85%, 41.35%]	21.53% [7.58%, 43.85%]
C. No change	9.38% [2.35%, 24.60%]	8.00% [2.04%, 21.05%]
- Leisure		
Alternative	Lower-income group	Higher-income group
A. Reschedule	30.84% [14.59%, 48.26%]	29.15% [14.72%, 47.54%]
B. Reduce/Drop	38.06% [19.24%, 55.56%]	46.15% [25.11%, 63.23%]
C. No change	31.10% [11.27%, 59.42%]	24.70% [8.16%, 50.43%]
- Work		
Alternative	Lower-income group	Higher-income group
A. Reschedule	57.40% [31.09%, 76.59%]	54.15% [30.11%, 73.76%]
B. Reduce/Drop	26.43% [11.03%, 48.90%]	26.90% [11.22%, 47.13%]

C. No change	16.17% [3.92%, 38.87%]	18.94% [5.91%, 41.15%]
Household average energy profile reshaping (kWh/month)		
Alternative	Lower-income group	Higher-income group
Rescheduled in Alternative A	21.45	22.55
Reduced in Alternative B	11.46	12.52
Remain in Alternative C	10.78	12.77
Household average savings and payments (£/month)		
Alternative	Lower-income group	Higher-income group
A. reschedule saving	5.48	5.77
B. Reduce saving	5.22	5.69
Total saving	10.70	11.47
Total Payment	20.36	22.51
Percentage saving	34.44%	33.75%

7.4.2.2 Presence of children

Households are also grouped based on the presence of at least one child under 18 years old. About 913 households do not live with children and 420 households live with at least one child. The results in Table 7.17 show that households with children are more flexible in the timing of activities “Cook hot meals”, “Boil drinking water” and “Work” but are less flexible in “Use a washing machine” during the afternoon peak (16:00-20:00). These differences are hard to be explained due to the nonlinear relationship between living with children and other variables. One potential reason is that, since the average school day in the UK ends at 3 or 4 pm, activities “Cook hot meals”, “Boil drinking water” and “Work” can be rescheduled before or around the end time of school. The percentage saving shows that households with children are more influenced by ToU tariffs.

Table 7.17 Results of groups with and without children

Alternative selection share		
- Cook hot meals		
Alternative	With child group	Without child group
A. Reschedule	32.49% [18.24%, 48.64%]	26.87% [14.50%, 41.98%]
B. Reduce/Drop	31.66% [18.03%, 47.09%]	37.78% [22.65%, 53.21%]
C. No change	35.84% [20.35%, 53.10%]	35.35% [20.00%, 52.77%]
- Boil drinking water		
Alternative	With child group	Without child group

A. Reschedule	32.83% [15.07%, 52.09%]	29.83% [12.67%, 50.51%]
B. Reduce/Drop	58.71% [37.79%, 75.49%]	56.37% [32.55%, 74.12%]
C. No change	8.46% [2.08%, 25.80%]	13.80% [3.60%, 37.05%]
- Shower		
Alternative	With child group	Without child group
A. Reschedule	42.13% [25.55%, 58.90%]	41.15% [24.03%, 57.25%]
B. Reduce/Drop	44.75% [27.02%, 61.38%]	44.19% [26.98%, 61.71%]
C. No change	13.12% [4.44%, 29.07%]	14.66% [4.99%, 31.91%]
- Use a washing machine		
Alternative	With child group	Without child group
A. Reschedule	67.31% [42.17%, 83.83%]	72.65% [49.08%, 87.62%]
B. Reduce/Drop	22.16% [7.83%, 45.78%]	19.88% [6.65%, 40.80%]
C. No change	10.53% [2.82%, 25.62%]	7.47% [1.77%, 21.02%]
- Leisure		
Alternative	With child group	Without child group
A. Reschedule	30.12% [15.56%, 47.76%]	29.88% [14.86%, 48.17%]
B. Reduce/Drop	46.69% [26.22%, 64.09%]	40.45% [20.83%, 57.90%]
C. No change	23.19% [7.35%, 48.37%]	29.67% [10.29%, 56.67%]
- Work		
Alternative	With child group	Without child group
A. Reschedule	58.69% [34.59%, 76.95%]	53.99% [28.10%, 74.18%]
B. Reduce/Drop	26.72% [11.26%, 46.62%]	26.67% [10.96%, 47.49%]
C. No change	14.59% [4.25%, 34.96%]	19.34% [5.77%, 43.31%]
Household average energy profile reshaping (kWh/month)		
Alternative	With child group	Without child group
Rescheduled in Alternative A	23.95	20.98
Reduced in Alternative B	12.54	11.77
Remain in Alternative C	10.64	12.35
Household average savings and payments (£/month)		
Alternative	With child group	Without child group
A. reschedule saving	6.13	5.38
B. Reduce saving	5.71	5.35
Total saving	11.83	10.73
Total Payment	21.86	21.28
Percentage saving	35.11%	33.52%

7.4.2.3 UK regions

The predicted results of households grouped based on UK regions, such as the regions of England and other authority areas, are shown in Table 7.18. The selection rates of Alternative C “No change” across groups are compared to show flexibility, with the highest and lowest shares underlined. Households in Northern Ireland have a distinctively high preference for not changing the patterns of activities “Cook hot meals”, “Boiling drinking water”, “Use a washing machine” and “Leisure. On the contrary, households in Northern Ireland are most flexible about the activity “Shower” and households in Scotland are least flexible about this activity. Households in the North East are most flexible in activities “Cook hot meals” and “Boil drinking water” but are least flexible in “Work”. Considering all six indoor activities, households in Northern Ireland save less from ToU tariffs. The explanation of these differences due to UK regions may involve geography, society, economy, culture and lifestyle, which is beyond the scope of this thesis. This can be the subject of further interdisciplinary research in collaboration with researchers in social science. It is also important to keep in mind the relatively small sample sizes on which these results are based.

Table 7.18 Results of UK region groups

Sample size												
	East of England	South East	South West	Greater London	West Midlands	East Midlands	Yorkshire and the Humber	North East	North West	Wales	Scotland	Northern Ireland
	112	178	122	185	119	87	120	47	154	61	141	19
- Cook hot meals												
Alternative	East of England	South East	South West	Greater London	West Midlands	East Midlands	Yorkshire and the Humber	North East	North West	Wales	Scotland	Northern Ireland
A. Reschedule	28.65% [15.99%, 44.15%]	30.82% [17.56%, 46.63%]	25.40% [13.12%, 39.94%]	29.39% [16.24%, 44.94%]	31.67% [17.85%, 47.31%]	29.65% [16.48%, 45.80%]	27.34% [14.70%, 42.38%]	31.42% [17.71%, 47.18%]	27.44% [14.95%, 42.90%]	27.10% [14.47%, 42.69%]	28.02% [15.41%, 43.65%]	19.66% [9.82%, 33.94%]
B. Reduce/Drop	36.17% [21.55%, 51.65%]	36.18% [21.74%, 50.91%]	35.51% [21.37%, 51.26%]	32.39% [19.12%, 46.77%]	38.06% [23.00%, 53.53%]	35.60% [20.64%, 51.65%]	35.21% [21.04%, 50.93%]	42.58% [26.98%, 58.02%]	36.27% [21.93%, 51.59%]	36.33% [20.88%, 51.85%]	36.89% [22.55%, 52.10%]	28.63% [15.19%, 44.62%]
C. No change	35.18% [20.28%, 51.90%]	32.99% [17.99%, 50.83%]	39.09% [23.22%, 55.75%]	38.22% [22.43%, 55.43%]	30.27% [16.30%, 47.83%]	34.75% [19.42%, 52.15%]	37.45% [22.11%, 53.99%]	<u>26.00%</u> [13.14%, 42.68%]	36.29% [21.05%, 53.02%]	36.57% [20.95%, 54.89%]	35.09% [19.92%, 51.76%]	<u>51.71%</u> [31.71%, 70.03%]
- Boil drinking water												
Alternative	East of England	South East	South West	Greater London	West Midlands	East Midlands	Yorkshire and the Humber	North East	North West	Wales	Scotland	Northern Ireland
A. Reschedule	30.91% [13.31%, 52.29%]	32.91% [15.02%, 53.32%]	31.21% [14.04%, 50.55%]	30.38% [13.25%, 50.32%]	32.70% [13.70%, 53.77%]	31.53% [14.18%, 52.64%]	30.67% [13.20%, 50.55%]	26.69% [11.21%, 47.15%]	29.61% [12.61%, 49.95%]	30.67% [13.53%, 51.36%]	29.28% [12.86%, 47.26%]	26.85% [10.64%, 47.22%]
B. Reduce/Drop	56.03% [31.91%, 74.12%]	54.98% [32.52%, 73.59%]	54.91% [32.92%, 72.87%]	59.27% [36.34%, 76.78%]	54.82% [32.84%, 72.93%]	56.28% [33.54%, 74.41%]	56.08% [33.64%, 74.26%]	65.50% [41.26%, 81.63%]	57.79% [35.68%, 75.79%]	57.11% [34.80%, 74.89%]	59.52% [38.10%, 76.81%]	57.58% [35.02%, 76.38%]

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C. No change	13.06% [3.42%, 34.86%]	12.11% [2.88%, 32.39%]	13.87% [3.44%, 35.90%]	10.35% [2.41%, 30.38%]	12.48% [3.22%, 33.53%]	12.19% [3.31%, 31.50%]	13.26% [3.43%, 35.33%]	7.81% [1.59%, 26.10%]	12.60% [2.85%, 33.22%]	12.23% [3.04%, 32.23%]	11.20% [2.98%, 30.42%]	15.57% [4.19%, 36.29%]
- Shower												
Alternative	East of England	South East	South West	Greater London	West Midlands	East Midlands	Yorkshire and the Humber	North East	North West	Wales	Scotland	Northern Ireland
A. Reschedule	42.65% [24.70%, 58.24%]	41.85% [24.20%, 57.85%]	40.50% [23.77%, 56.49%]	39.01% [22.14%, 54.80%]	41.94% [24.82%, 57.17%]	44.35% [25.88%, 59.81%]	41.27% [24.24%, 56.85%]	41.18% [23.40%, 57.32%]	40.98% [23.02%, 57.16%]	42.11% [24.70%, 58.07%]	42.27% [24.83%, 58.18%]	39.66% [23.14%, 57.65%]
B. Reduce/Drop	43.53% [26.23%, 61.40%]	44.75% [27.47%, 62.15%]	46.09% [28.53%, 62.93%]	45.37% [27.04%, 62.93%]	42.22% [25.57%, 60.01%]	44.72% [27.77%, 62.27%]	45.56% [27.98%, 63.10%]	43.07% [26.20%, 60.04%]	44.54% [26.45%, 62.55%]	45.35% [27.97%, 62.71%]	41.44% [24.85%, 59.38%]	55.26% [35.39%, 71.59%]
C. No change	13.82% [4.46%, 32.52%]	13.39% [4.88%, 30.03%]	13.41% [4.57%, 30.96%]	15.62% [5.35%, 34.96%]	15.85% [6.29%, 32.33%]	10.93% [3.67%, 26.65%]	13.17% [4.36%, 30.56%]	15.75% [6.09%, 33.50%]	14.48% [5.16%, 32.96%]	12.54% [4.02%, 29.32%]	16.29% [5.81%, 34.16%]	5.08% [1.14%, 16.25%]
- Use a washing machine												
Alternative	East of England	South East	South West	Greater London	West Midlands	East Midlands	Yorkshire and the Humber	North East	North West	Wales	Scotland	Northern Ireland
A. Reschedule	70.82% [46.73%, 85.44%]	72.57% [48.84%, 87.14%]	71.40% [46.95%, 86.31%]	71.75% [48.66%, 86.96%]	69.68% [45.67%, 85.02%]	72.18% [48.45%, 86.74%]	70.43% [45.24%, 86.20%]	69.81% [44.38%, 85.86%]	69.88% [44.15%, 85.45%]	69.44% [44.75%, 85.98%]	68.58% [43.51%, 85.31%]	65.71% [40.79%, 82.80%]
B. Reduce/Drop	20.70% [7.72%, 41.33%]	20.23% [7.19%, 41.66%]	18.99% [6.70%, 39.11%]	21.18% [7.56%, 42.78%]	22.77% [8.66%, 44.59%]	18.39% [6.08%, 40.36%]	21.41% [7.12%, 44.50%]	22.91% [7.53%, 46.54%]	20.20% [6.93%, 43.65%]	21.81% [7.10%, 45.93%]	21.56% [7.46%, 44.18%]	19.85% [6.16%, 44.41%]
C. No change	8.47% [2.17%, 23.27%]	7.20% [1.78%, 19.94%]	9.61% [2.25%, 26.57%]	7.07% [1.74%, 19.04%]	7.55% [1.85%, 21.12%]	9.43% [2.27%, 23.54%]	8.16% [1.93%, 22.60%]	7.28% [1.76%, 20.98%]	9.92% [2.60%, 25.35%]	8.75% [2.12%, 21.55%]	9.86% [2.61%, 24.56%]	14.43% [3.64%, 31.37%]
- Leisure												

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Alternative	East of England	South East	South West	Greater London	West Midlands	East Midlands	Yorkshire and the Humber	North East	North West	Wales	Scotland	Northern Ireland
A. Reschedule	30.48% [15.22%, 48.19%]	31.63% [15.64%, 50.69%]	29.57% [14.60%, 46.59%]	28.81% [14.18%, 47.03%]	31.73% [16.22%, 49.64%]	32.16% [15.93%, 50.07%]	27.33% [13.19%, 45.51%]	30.80% [15.95%, 49.19%]	29.63% [14.82%, 46.79%]	30.91% [15.54%, 48.70%]	28.39% [14.00%, 46.54%]	28.41% [13.09%, 45.92%]
B. Reduce/Drop	39.83% [20.50%, 57.29%]	40.64% [20.99%, 57.75%]	39.41% [20.47%, 57.23%]	44.15% [22.91%, 61.62%]	43.04% [22.74%, 59.82%]	43.34% [22.93%, 60.15%]	41.75% [21.54%, 58.84%]	44.71% [24.33%, 61.03%]	43.44% [23.56%, 61.18%]	42.21% [22.43%, 59.17%]	44.07% [23.37%, 60.87%]	40.02% [22.51%, 57.16%]
C. No change	29.69% [10.36%, 56.54%]	27.73% [9.16%, 55.01%]	31.03% [11.23%, 57.52%]	27.04% [9.19%, 54.01%]	25.23% [8.53%, 51.67%]	<u>24.49%</u> <u>[8.15%, 52.12%]</u>	30.92% [11.12%, 58.14%]	24.49% [8.25%, 50.31%]	26.92% [9.20%, 53.11%]	26.88% [9.20%, 53.51%]	27.54% [9.69%, 54.23%]	<u>31.57%</u> <u>[11.97%, 57.35%]</u>
- Work												
Alternative	East of England	South East	South West	Greater London	West Midlands	East Midlands	Yorkshire and the Humber	North East	North West	Wales	Scotland	Northern Ireland
A. Reschedule	55.42% [30.70%, 75.30%]	53.61% [28.63%, 75.15%]	56.58% [31.13%, 76.13%]	55.33% [30.54%, 75.07%]	56.89% [32.03%, 75.75%]	54.86% [28.79%, 75.45%]	57.96% [33.20%, 76.73%]	45.53% [22.98%, 66.31%]	56.73% [32.29%, 76.05%]	59.02% [33.62%, 77.68%]	55.37% [31.35%, 74.89%]	55.77% [31.53%, 75.51%]
B. Reduce/Drop	27.20% [11.33%, 47.12%]	27.04% [11.20%, 47.51%]	23.15% [9.62%, 42.60%]	26.96% [10.69%, 48.35%]	26.22% [11.21%, 47.27%]	29.32% [11.95%, 52.77%]	25.87% [10.59%, 46.62%]	32.80% [14.61%, 55.24%]	25.99% [10.93%, 46.37%]	27.70% [11.68%, 49.16%]	25.70% [10.63%, 45.39%]	30.58% [14.02%, 50.85%]
C. No change	17.38% [5.14%, 39.09%]	19.35% [5.68%, 41.63%]	20.27% [6.46%, 42.75%]	17.70% [4.75%, 41.11%]	16.89% [4.70%, 38.78%]	15.81% [4.00%, 36.98%]	16.17% [4.37%, 38.37%]	<u>21.67%</u> <u>[6.10%, 45.37%]</u>	17.28% [5.26%, 38.21%]	<u>13.28%</u> <u>[3.56%, 34.05%]</u>	18.94% [5.68%, 41.51%]	13.65% [3.81%, 31.81%]
Household average energy profile reshaping (kWh/month)												
Alternative	East of England	South East	South West	Greater London	West Midlands	East Midlands	Yorkshire and the Humber	North East	North West	Wales	Scotland	Northern Ireland
A. Reschedule	23.53	22.13	21.90	20.07	21.94	23.75	22.78	19.70	21.11	21.05	22.98	21.72

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B. Reduce/ Drop	12.38	11.66	11.94	11.20	11.51	12.36	12.42	12.24	12.02	11.77	13.07	12.65
C. No change	12.76	11.65	13.01	11.14	10.64	11.12	12.56	9.51	11.74	11.10	12.68	14.74
Household average savings and payments (£/month)												
Alternative	East of England	South East	South West	Greater London	West Midlands	East Midlands	Yorkshire and the Humber	North East	North West	Wales	Scotland	Northern Ireland
A. Reschedule	6.02	5.66	5.61	5.14	5.61	6.08	5.83	5.05	5.41	5.39	5.89	5.57
B. Reduce/ Drop	5.63	5.31	5.44	5.10	5.24	5.63	5.65	5.56	5.47	5.35	5.95	5.76
Household average total saving (£/month)												
	11.66	10.97	11.05	10.24	10.85	11.70	11.49	10.61	10.87	10.74	11.83	11.33
Household average total Payment (£/month)												
	22.57	21.08	21.92	19.99	20.44	21.85	22.37	20.22	21.28	20.74	23.10	23.35
Percentage saving												
	34.06%	34.23%	33.52%	33.87%	34.68%	<u>34.87%</u>	33.93%	34.41%	33.81%	34.12%	33.87%	32.67%

7.5 Discussion and limitations

7.5.1 WTA and WTP

Analysing the disparity between WTA and WTP is essential for choosing the appropriate value measures to assess the economic consequences (Koetse & Brouwer, 2016). There is abundant empirical evidence of loss aversion in the literature. In psychology and behavioural economics, the endowment effect presented that people are more likely to retain an object they own than acquire that same object when they do not own it. The endowment effect implies that people treat opportunity costs differently than out-of-pocket costs. In other words, foregone gains are less painful than perceived losses (Kahneman, Knetsch & Thaler, 1991). Similarly, a key element of prospect theory is people value losses higher than gains, leading to a disparity between WTA and WTP (Koetse & Brouwer, 2016).

The results of this chapter also show consumers' different perceptions regarding saving and payment. The coefficients of value change measured by saving are not significant while coefficients of payment are significant. One reason could be the loss aversion as stated in the literature and another reason is the relatively small savings and large payments. Conventional choice models use the ratio of coefficients to calculate WTA/WTP for attributes. However, the insignificant coefficients in the estimated choice models make it difficult to find a proper ratio of coefficients for comparison. Despite the difficulty, the WTA for rescheduling indoor activities to different off-peak hours is shown in Table 7.19, excluding the ratios with insignificant coefficients. This table shows that the WTA for rescheduling "Cooking hot meals" and "Shower" are higher than that of rescheduling other activities. The small WTA of rescheduling "Work" may result from the fact that this off-peak period aligns with the working time before the adaptation.

Table 7.19 "Willingness to accept" value of rescheduling time

Activity	WTA (£/month) for rescheduling the activity to	
	Off-peak 2, 13:00 - 16:00	Off-peak 3, 20:00 - 22:00
Cook hot meals	4.10	
Boil drinking water	0.97	-
Shower	-	3.10
Use a washing machine	1.17	
Work	1.32	-

7.5.2 Comparison with findings from ToU tariff experiments

ToU tariffs and DSM programmes have been tested in the UK and the findings from these experiments are compared with the results of this chapter.

A review of the ToU experiments in Great Britain, Northern Ireland and Ireland from 2002 to 2020 (Torriti & Ramírez-Mendiola, 2022) pointed out the limitations of the prevailing interpretation of ToU tariffs. Energy economists tend to attribute unsuccessful price-driven interventions for changing electricity demand to inappropriate pricing strategies, but this neglects other factors that affect choice behaviour and decision-making. This common interpretation was also challenged by Öhrlund, Linné & Bartusch (2019) who stated that price signals do not significantly influence the willingness to participate in DSM. The results of this chapter provide proof for this argument by showing that the original activity time, the rescheduled activity time, the days of working/non-working, seasons and socio-demographics can play roles in activity adaptation.

The flexibility of indoor activities was also analysed in the literature. Laundry, household chores and dishwashing are usually considered as flexible. Showering, tumble drying and vacuum cleaning are mid-level flexible while cooking, eating and leisure activities are time-critical (Jack, 2017; Smale, Van Vliet & Spaargaren, 2017; UK Power Networks, 2014). Since models were built for each activity, there is no direct comparison between the flexibility of indoor activities in this chapter. However, the WTA value for rescheduling indoor activities calculated in the previous section shows similar results in that cooking and showering are hard to reschedule while the laundry can be rescheduled easily.

Low Carbon London (LCL 2010-2014), a 4-year innovation project, provides real household responses to dynamic ToU signals. The project reports (UK Power Networks, 2014; Schofield et al., 2014) show that household responses are related to the seasons, day of the week and time of the day, supporting the findings of this chapter. In addition, LCL reveals that Sundays contribute to a greater response to off-peak prices and households change more demand during the waking hours of the day (7 am-midnight). Similarly, in this chapter, non-working days increase the probability of adapting patterns of several indoor activities and the off-peak hours (midnight-5 am) are less

preferred. However, in LCL, households in winter and spring months change their electricity consumption more, which is opposite to the positive impact of the warm season in this chapter. This difference in seasonal effect could potentially be due to the inclusion of electricity for heating in LCL.

The distributional impact of ToU tariffs was also investigated in a study by Yunusov & Torriti (2021). They identified the impacts of introducing ToU tariffs on different socio-demographic groups. ToU tariffs in their study and the Economy 10 tariff used in this chapter do not have the same distribution of off-peak hours but both have peak hours 16:00-20:00. Assuming no behavioural change, Yunusov & Torriti (2021) found similar distributional impacts as this chapter that ToU tariffs would benefit financially single parents in the low-income group compared with standard flat tariff. That analysis based on no behavioural change can be combined with this chapter which focuses on behavioural change to have a comprehensive understanding of both financial and behavioural change derived from the introduction of ToU tariffs.

7.5.3 Limitations

There are three limitations of the study in this chapter. First, the design of the DSM-SP survey can be improved in terms of sample size, attributes considered and survey flow. The overall sample size of about 1333 participants is not small compared with previous research. However, the twelve blocks of hypothetical situations limit the size of each block. In addition, the choice situations in the SCEs involve a large number of attributes that challenge participants' ability to fully consider all factors. What is more, the DSM-SP survey contains questions about current tariffs, activity schedules, attitudes and choice situations in various contexts, which may fatigue participants and distort responses. Some feedback from participants states that the survey is long and it is difficult to consider all variables at the same time, such as the season, working/non-working days, the original and new time of activities, and saving/payment. Therefore, the impacts of attributes may not be fully captured and the gap between stated preference and real situations may be widened. Increasing the sample size and focusing on particular contexts may address this limitation in future work.

Second, more factors can be designed and integrated into the choice model to reduce uncertainty. Although many attributes have been included in hypothetical situations, this chapter does not capture the impact of participants' daily schedules. The choice of

adapting activities is inherently complex and one of the main influential factors is whether the new schedule conflicts with other activities. However, the detailed time-use of participants is not collected in the DSM-SP survey. In addition, the rescheduling of indoor activities was simplified to the change of a single activity while more complex possibilities were ignored, such as exchanging the timings of two indoor activities and the potential ripple effects of rearranging activities. As stated in Section 7.3.2.7, a substantial amount of unobserved preference heterogeneity is detected in the models. Therefore, more attributes such as the attitudes of participants, household appliance ownership and electricity bills can be explored with other models such as the hybrid choice models. In summary, new models and novel attributes of daily schedules need to be designed to better understand these choices.

Third, the case study, as the application of choice models, does not consider the penetration rate of ToU tariffs and consumer satisfaction. When the electricity price changes and influences the potential benefit of consumers, the penetration rate of the ToU tariffs may change, which will impact the effectiveness of DSM. Although this kind of choice behaviour has been studied in the literature, it is not integrated into the case study in this chapter. Consumer satisfaction and well-being in activity adaptation is another issue that needs to be studied. As the distributional impact analysis in the case study shows, ToU tariffs may force households with lower incomes to have a more disrupted schedule of essential indoor activities though with a correspondingly higher monetary benefit. However, given the limited sample size employed in estimating mixed logit models, this conclusion needs to be validated in larger datasets.

7.6 Summary

This chapter is among the first to model the behaviours of activity adaptation in response to ToU tariffs and to quantify the influential factors by building choice models based on data from an SP survey. This DSM-SP survey recruited 1333 participants across the UK. Six common indoor activities were studied in the contexts of cold/warm seasons and working/non-working days. The exploratory analysis of the DSM-SP survey describes the characteristics of participants in terms of electricity tariffs, activity schedules, as well as attitudes toward energy conservation and ToU tariffs. The choices in hypothetical situations are used to build discrete choice models and quantify the

impacts of various attributes. The main findings are summarised below based on the analysis in Sections 7.2.2, 7.3.2 and 7.4.2:

- (1) Both the reported previous experiences and the choices in hypothetical situations indicate a preference among participants to maintain the original activity schedules even with the introduction of the ToU tariffs.
- (2) The timing of the original activity and the rescheduled activity plays an important role in the activity adaptation. In the waking time of the day (05:00-13:00 and 16:00-20:00), activities “Cook hot meals”, “Boil drinking water” and “Work” are less likely to be rescheduled, while activities “Use a washing machine” and “Leisure” demonstrate a higher possibility to be adapted. As for the new activity time after rescheduling, “Shower” is preferred to be undertaken at night (20:00-22:00). Other indoor activities are slightly preferred during the afternoon (13:00-16:00). As expected there is no preference for indoor activities to be rescheduled to the time after midnight (00:00-05:00) indicating that these off-peak hours are hard to be utilised by consumers. On the contrary, due to the low demand at these hours, shifting demand to these periods is encouraged by electricity providers.
- (3) Participants are sensitive to the payments they are charged for the electricity consumed by activities but not as sensitive to savings arising from adapting activity schedules. Therefore, when promoting ToU tariffs, it may be more effective to emphasize the comparison between electricity bills before and after switching to ToU tariffs, rather than solely focusing on savings.
- (4) The case studies suggest that potential household savings, ranging from 8.85 to 13.04 £/month, may motivate consumers to reduce peak loads in the afternoon peak hours. More than half of the loads driven by the six activities studied in this chapter are either rescheduled or reduced, accounting for about 32.10 to 36.25 kWh/month.
- (5) The distributional impact analysis of case studies shows that households with lower income obtain more savings through activity adaptation in ToU tariffs but with the sacrifice of a more disrupted schedule of essential indoor activities. Similarly, households with children are more impacted by ToU tariffs. In addition, households in particular regions in the UK, such as Northern Ireland, exhibit distinct patterns in activity adaptation.

The most novel contribution of this chapter is in introducing choice models to this discipline and quantitatively modelling the activity adaptation behaviours in response to ToU tariffs. The case studies show that these models can be used to predict consumer responses in DSM and then assess the potential for improvements in energy saving. In addition, the findings above can provide insights into the design of ToU tariffs, DSM projects and energy policies.

Chapter 8

CONCLUSIONS

8.1 Overview

Energy demand modelling and demand-side management (DSM) have been extensively studied for years to enhance energy efficiency, balance supply and demand, and upgrade electricity network management. However, with the expansion of intermittent renewable energy generation and the increasing demand for electric vehicle (EV) charging, both challenges and opportunities have emerged in DSM, particularly within the residential sector. Although researchers have begun to consider the impact of EV charging demand, the travel activities behind the electricity consumption of EVs have not been connected to the conventional indoor activities in energy demand modelling and DSM. Due to the limitation of data accessibility, the estimation of interrelated components, such as travel and indoor activities, as well as EV charging demand and indoor electricity demand, is usually estimated based on data from disparate contexts. Moreover, consumer behaviours and indoor activities that drive indoor electricity consumption are usually simplified or neglected in DSM. In particular, the relationship between activity and electricity consumption is usually modelled with conversion factors based on the type of activity, whilst other influential factors such as the time of the day and the interaction between simultaneous activities are disregarded. Machine learning models, which are famous for their capacity to capture nonlinear relationships, are rarely utilised in this domain because of the lack of simultaneous activity records and electricity consumption records. Lastly, a fundamental assumption in DSM is that participants will adapt their activity patterns in response to price signals or incentives. However, these responsive behaviours are commonly taken for granted while other considerations such as the season and the timing of activities, apart from saving and satisfaction, are frequently ignored. These gaps could contribute to bias in the assessment of DSM, potentially leading to failures in achieving energy-saving goals.

To address these gaps, this thesis first presents four objectives and then achieves them in the subsequent chapters:

- (1) Objective A: Introduce the connection between consumer indoor activities and travel activities in load profile generation models.

Chapter 4 designs a load profile generation framework that can simulate coordinated indoor load profiles and EV charging load profiles. The connection between travel activities and indoor activities is captured based on cohesive household activity profiles that incorporate both types. Consequently, the impacts of generated EV charging loads on meter-recorded household indoor loads in the same context are analysed across three charging scenarios.

- (2) Objective B: Assess different methods and develop guidelines and recommendations for ML-based load profile models.

Chapter 5 tests six popular machine learning models in multiple scenarios of energy demand modelling. A novel feature “TimeCredit” is designed to capture the impacts of interactions from simultaneous indoor activities. Practical guidelines are provided for selecting the optimal algorithms, model inputs and the width of the historical time window. This chapter also answers another related research question: Where it is worth using electricity demand data with rich information about households and their activities in energy demand modelling.

- (3) Objective C: Design a hybrid DSM model that considers consumer activities and interactions between them.

Chapter 6 builds a hybrid DSM optimisation model that incorporates the framework in Chapter 4 (Objective A) and the best-performing models from Chapter 5 (Objective B). Thus, the cohesive activity profiles, as well as multiple factors that influence demand, such as activity start times and the interaction between activities are incorporated. Additionally, the potential bias arising from the neglect of the connection between travel activities and indoor activities is explored by testing the results of observed and simulated activity profiles.

- (4) Objective D: Generate new evidence and models that help us to better understand consumer behaviour in the context of DSM.

Chapter 7 conducts a stated preference survey, DSM-SP, to collect data on the consumer choices of adapting household activities in response to time of use (ToU) tariffs in hypothetical situations. Based on the DSM-SP survey, discrete choice models

are built to study the influential factors such as activity start time, electricity prices and socio-demographics. In addition, case studies are designed where the estimated choice models are used to predict consumer responses to different ToU price levels and explore the distributional impacts.

8.2 Summary of works and contributions

This thesis has studied and bridged the stated gaps through the detailed representation of consumer activities and behaviours in energy demand modelling and DSM. The results provide valuable contributions to both the academic and practical aspects of this field. The works and contributions are summarised below.

- (1) Conceptual: This PhD research represents one of the pioneering works in the field, introducing and emphasising three novel concepts in energy demand modelling and DSM. First, the connection between travel activities and indoor activities should be considered. Neglecting this connection can introduce bias in both energy demand modelling and DSM. Second, the nonlinear relationship between indoor activities and electricity consumption should be modelled with other influential factors, such as the activity start times, electricity prices and socio-demographics. Conventional relationships with conversion factors fail to capture the impact of factors other than the activity type. Third, consumers' activity adaptation in DSM should be studied beyond the energy saving and ranges of activity start times to understand other influential factors and real choices. These three conceptual novelties guide this PhD research and highlight the roles of consumer activities and behaviours in this field.
- (2) Data: This PhD research incorporates various datasets from transport surveys, time-use surveys, sensor monitoring records and stated preference surveys. The METER dataset is explored to highlight the importance of simultaneous activity records and electricity records while the absence of end times of activities poses a challenge in modelling. The travel records in the METER and LTDS datasets, as well as the car parking records in Singapore, reveal that travel patterns, such as car parking timings and travel distance, may not follow the normal distribution commonly assumed in the literature. Vehicles also tend to have multiple daily parking records throughout the day. Consequently, the EV charging demand estimated based on empirical probability distributions, may

either exaggerate the number of vehicles or lose the information on multiple parking events caused by the same vehicles. The state preference survey stands out by presenting consumers' activity schedules, attitudes toward ToU tariffs and activity adaptation in hypothetical situations. To the best of my knowledge, it is the only application of SP methods in studying specific activity adaptation in DSM research to date.

- (3) Methodological: The framework developed in this thesis incorporates both EV charging loads and household indoor loads in the same context for energy demand modelling and DSM. Multiple energy demand models are tested including conventional models with conversion factors and machine learning models based on meter-related data and survey-related data. Scenarios with different inputs and model settings are tested to identify the best-performing algorithms and optimal dataset structures. In addition, a novel feature "Time credit" is designed to offset the sparsity of activity records and the absence of activity end times in the dataset, as well as to represent the interaction between simultaneous activities. The results show that short-term meter-related features are sufficient to predict electricity consumption, while survey-related features can make the model robust against sudden load variations. Amongst the various algorithms tested, LightGBM and ANN outperform others in the multi-household datasets. This PhD research also takes a pioneering role by utilising choice models to study and predict consumers' adaptation of indoor activities in DSM. Specific attributes and alternatives are designed for this new context of choice models.
- (4) Application: This PhD research demonstrates the application of the designed framework in the impact analysis of EV charging demand, the assessment of DSM and the estimation of ToU tariff benefits. The impact analysis of EV charging demand with the framework in this thesis captures the connection between travel behaviours and indoor activities. It also allows for testing the influence of different charging strategies and locations. The results show that limiting the charging rate may be more efficient than adding charging locations in mitigating the increase of peak loads. Testing DSM through hybrid optimisation models with different tariffs highlights the need for careful design in the distribution of peak and off-peak hours to avoid the contradiction between

minimising cost and PAR. The estimated choice models indicate that participants are sensitive to the payments they are charged but not as sensitive to savings arising from adapting activity schedules. Therefore, when promoting ToU tariffs, it may be more effective to emphasize the comparison between electricity bills before and after switching to ToU tariffs, rather than solely focusing on savings. The case study using choice models predicts the adaptation of activity schedules during the afternoon peak under different ToU price scenarios. The electricity bill savings, the demand shift and the distributional impacts on income level, households with children and geographical locations can be estimated based on the results, providing insights into the design of ToU tariffs and DSM.

8.3 Limitations and future work

The limitations in each component of this PhD research are explored in detail at the end of their respective chapters. This section aims to summarise broad limitations from the perspectives of datasets and models. Additionally, potential avenues for future work are discussed.

The accessibility of data remains a significant challenge in this area of research. Two main datasets used in this PhD research, the METER dataset and the SP survey, are substantially novel but share several drawbacks. The sample sizes of these two datasets are relatively small in certain aspects and the absence of important information introduces uncertainty in the models. For example, the METER dataset is not representative of the general population. In addition, the monitoring period of thirty hours per household is short, and the lack of end time of activities is a notable deficit. The relatively large number of blocks in the SP survey results in a limited size per block. Smart sensors such as smart plugs may partly address this limitation by providing accurate records of appliance usage.

One shared limitation of models in this PhD research is the absence of validations in larger datasets, which is also related to the rarity of large novel datasets. This limitation also persists in the broader literature as many models are validated only at the aggregated level or with a limited number of households (Widén et al., 2009). The limitation of datasets and the failure to capture critical influential factors in models results in uncertainties. One example is the uncertainty about the designed features

“TimeCredit” and the large errors in machine learning models. The uncertainty is also shown as the significant error terms of panel effects in the choice models and the large confidence intervals in the case study. The lack of model validations in larger datasets may result in biased estimation of influential factors and conclusions that are not general across populations. For example, the impacts of weather features are not captured in Chapter 5 due to the lack of data for heating and cooling. In addition, the distributional impacts in UK regions with fewer participants in Chapter 7 may not be reliable.

The connections between consumers’ travel activities, indoor activities and behaviours in DSM can be further studied based on this thesis. Firstly, this thesis considered static occupancy schedules in energy demand models and DSM, indicating the times of leaving and arriving home remain unaffected by DSM. However, research has shown that occupancy schedules are not static (Daina, 2014). Hence, the flexible occupancy schedule needs to be integrated into the energy demand models, choice models and DSM. Secondly, consumer satisfaction and the choice to participate in DSM can be studied based on the choice model and integrated into the evaluation of DSM. Instead of assumed satisfaction, simple ranges of activity start time and no withdrawal from DSM, consumers’ feelings and willingness to participate can be integrated with choice models to obtain a more comprehensive evaluation of DSM. Thirdly, models developed in this PhD research can be combined to simulate the real operation of DSM. For example, agent-based simulation or reinforcement learning can utilise choice models and energy demand models to generate both activity schedules and load profiles under cooperative or noncooperative strategies in DSM.

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Appendix 1: Features in the METER dataset after processing

Feature Category		Feature	Description
Calendar		Weekday	-
		Month	-
		BankHoliday	-
		Year	-
		Minute(sin)	-
		Minute(cos)	-
Meter-related	Smart meter record	Watt	-
	Smart meter record-statistics	Watt (average)	-
		Watt (maximum)	-
		Watt (minimum)	-
		Watt (median)	-
		Watt (25% percentile)	-
		Watt (75% percentile)	-
		Watt (standard deviation)	-
Other energy-related	Weather	Air temperature	-
		Dewpoint	-
		Relative humidity	-
	Energy tariff	EnergyType	The type of energy tariff
		EnergyTypePeak	Indicator of peak time
		StandingEnergyTariff	Fixed cost of the tariff (in GBP)
		EnergyConsumptionTariff	kWh cost of the tariff (in 0.01 GBP, i.e. pence)
	Household and individual attributes	People	How many people live in the household?
		age_group_i (i =1, 2, 3, 4, 5,6)	How many of you are in each age group?
		house_type	What type of house do you live in?
		rooms	How many rooms does your home have?
		own	Do you own or rent your property?
		income	What is your household income?
		Student	How many of you are in each occupation group?
		Employed	
		Self-employed	
		Volunteer	

Energy Demand Modelling and Demand-Side Management with Detailed Representation of Consumer Activities and Behaviours

		Unemployed	Appliance ownership
		Electric car	
		Solar thermal	
		PV panels	
		Electricity display	
		Electric hob	
		Gas boiler	
		Heatpump	
		Underfloor heating	
		Washer dryer	
		Tumble dryer	
		Washing machine	
		Dehumidifier	
		Airconditioner	
		Portable heaters	
		Night storage heaters	
		Power shower	
		TVcomputerscreens	
Survey-related	Appliance usage	kettle	“Peopleinvolved” and “TimeCredit” for each appliance and activity category
		making breakfast	
		making lunch	
		making dinner	
		hob	
		oven	
		tv	
		information and communication technology (ICT) products	
		Screen time (e.g., tablet, laptop)	
		shower	
		Microwave	
		toaster	
		other	
	General activity categories	care_self	
		food	
		recreation	
		work	
		care_other	
		care_house	
		other_category	

Appendix 2: Simplified Protocol of Designed Stated Preference Survey

Start of Block: Introduction

Q1.1 Thank you for agreeing to participate in this survey.

This survey focuses on understanding how people respond to different electricity tariffs (in pence/kWh) in terms of activity rescheduling.

Generally, there are two types of electricity tariffs:

- Single rate tariffs: You pay a flat rate for electricity regardless of the time of day.
- Time of Use tariffs (ToU tariffs, e.g., Economy 7): You pay different rates at different times of the day.

More ToU tariffs are offered nowadays to save energy and money. We will ask you to imagine how you will reschedule electricity-consuming household activities when switching to ToU tariffs. The results will help us analyse the impact of electricity tariffs on electricity bills and energy conservation.

The survey should take 15-25 minutes to complete. The data collected in this survey will be used for academic research purposes only. All information will be anonymised and kept confidential, and data handling will be as per GDPR compliant policies. If you have any questions about this survey or this study, please don't hesitate to contact hw2519@ic.ac.uk.

Note: If you are using your phone to answer the questionnaire, you might need to switch to landscape mode to ensure the best view throughout the survey.

Q1.2 Before moving on, please read below to give your formal consent to participate in the survey:

- I confirm that I have read and understand the participant information sheet version (click to read the [Participant Information Sheet Version 2.0 Date 17/08/2022](#)) for the research "Rescheduling household activities under the influence of Time of Use Tariffs in Demand Side Management" and have had the opportunity to ask questions which have been answered fully.

- I understand that my participation is voluntary, and I am free to withdraw at any time, without giving any reason and without my legal rights being affected

- I understand that data collected from me are a gift donated to Imperial College and that I will not personally benefit financially if this research leads to an invention and/or the successful development of a new test, medication treatment, product or service.

By continuing with the survey, you give your consent to the above. Do you wish to

continue?

- ☐ Yes
- ☐ No

Display This Question:

If Before moving on, please read below to give your formal consent to participate in the survey: - I... = Yes

Q1.3 Optional consent

Please read the following statements and indicate whether you would like to additionally give consent to the below.

	Yes	No
I give consent for information collected about me to be used to support other research by an academic institution or commercial company in the future, including that outside of the United Kingdom (Which Imperial has ensured will keep this information secure).	☐	☐
I give consent to being contacted about the possibility to take part in other research studies.	☐	☐

End of Block: Introduction

Start of Block: Screening questions

Q2.1 A few questions about you

This first section contains some questions that will allow us to see if you're one of the people we're looking to speak to for this research project.

Q2.2 Do you live in the United Kingdom (UK)?

- ☐ Yes
- ☐ No

Q2.3 How old are you?

- ☐ Under 18
- ☐ 18-24 years old
- ☐ 25-34 years old
- ☐ 35-44 years old
- ☐ 45-54 years old

- ☐ 55-64 years old
- ☐ 65+ years old
- ☐ Prefer not to answer

Q2.4 Which option best describes how your electricity bill is paid?

- ☐ Paid by yourself, partly or wholly, according to how much electricity you consume.
- ☐ Paid by another family member(s), relatives or friends
- ☐ Included in the rent or a fixed cost regardless of how much electricity you consume.
- ☐ Other. Please specify:

Q2.5 Have you undertaken each of the following activities **at home** at least once in the last month?

1. Cook hot meals (e.g., use electric hobs, microwave and electric oven)
 2. Boil drinking water (e.g., use electric kettles)
 3. Shower (e.g., use electric showers)
 4. Use a washing machine
 5. Work with electric appliances(e.g., laptop)
 6. Leisure with electric appliances(e.g., TV)
- ☐ Yes
 - ☐ No

Q2.6 Are you currently in a situation (e.g., physical or mental health conditions) that may make it difficult for you to change the timing and quality of the following activities?

1. Cook hot meals (e.g., use electric hobs, microwave and electric oven)
 2. Boil drinking water (e.g., use electric kettles)
 3. Shower (e.g., use electric showers)
 4. Use a washing machine
 5. Work with electric appliances(e.g., laptop)
 6. Leisure with electric appliances(e.g., TV)
- ☐ Yes
 - ☐ No

End of Block: Screening questions

Start of Block: Current schedule

Q3.1 This section is to learn more about your current electricity tariff and your current schedule of six types of activities:

1. Cook hot meals (e.g., use electric hobs, microwave and electric oven)
2. Boil drinking water (e.g., use electric kettles)
3. Shower (e.g., use electric showers)
4. Use a washing machine
5. Work with electric appliances(e.g., laptop)
6. Leisure with electric appliances(e.g., TV)

Q3.2 What type of electricity tariff do you have now in terms of prices during the day?

- ☐ Single rate tariffs: You pay a flat rate for electricity regardless of the time of day.
- ☐ Time of Use tariffs (e.g., Economy 7): You pay different rates at different times of the day.
- ☐ Not sure

Display This Question:

If What type of electricity tariff do you have now in terms of prices during the day? = Time of Use tariffs (e.g., Economy 7): You pay different rates at different times of the day.

Q3.3 What's your electricity price (per unit) now?

pence/ kWh	Below 20	20-25	25-30	30-35	35-40	Beyond 40	Not sure
Peak time rate (higher)	☐	☐	☐	☐	☐	☐	☐
Off-peak time rate (lower)	☐	☐	☐	☐	☐	☐	☐

Display This Question:

If What type of electricity tariff do you have now in terms of prices during the day? = Single rate tariffs: You pay a flat rate for electricity regardless of the time of day.

Q3.4 What's your electricity price (per unit) now?

pence/kWh	Below 20	20-25	25-30	30-35	35-40	Beyond 40	Not sure
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Single rate	☐	☐	☐	☐	☐	☐	☐
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Display This Question:

If What type of electricity tariff do you have now in terms of prices during the day? !=
Not sure

And If

- What's your electricity price (per unit) now? [Below 20 pence/kWh] (Count) > 0
 Or What's your electricity price (per unit) now? [20 – 25 pence/kWh] (Count) > 0
 Or What's your electricity price (per unit) now? [25 – 30 pence/kWh] (Count) > 0
 Or What's your electricity price (per unit) now? [30 – 35 pence/kWh] (Count) > 0
 Or What's your electricity price (per unit) now? [35 – 40 pence/kWh] (Count) > 0
 Or What's your electricity price (per unit) now? [Beyond 40 pence/kWh] (Count) > 0
 Or What's your electricity price (per unit) now? = Single rate [Below 20 pence/kWh]
 Or What's your electricity price (per unit) now? = Single rate [20 – 25 pence/kWh]
 Or What's your electricity price (per unit) now? = Single rate [25 – 30 pence/kWh]
 Or What's your electricity price (per unit) now? = Single rate [30 – 35 pence/kWh]
 Or What's your electricity price (per unit) now? = Single rate [35 – 40 pence/kWh]
 Or What's your electricity price (per unit) now? = Single rate [Beyond 40pence/kWh]

Q3.5 How sure are you about the electricity price you provided?

- ☐ Not sure
- ☐ Slightly sure
- ☐ Somewhat sure
- ☐ Moderately sure
- ☐ Definitely sure

Q3.6 We have four contexts:

1. **Main context:**

Working days



in the **cold** season



2. **Non-working days**



in the **cold** season



3. **Working days**



in the **warm** season



4. **Non-working days**



in the **warm** season



We will first ask about your schedule in the main context (#1).

Then the other three contexts may be asked based on how your activity schedule in them differs from the main context.

For example, if your frequency or timing of cooking hot meals is different in the warm season, we will give you the opportunity to provide the new schedule.



Q3.7 Main context - No.1

On a **working day**  in the **cold season** , e.g., from December to February, or the average low temperature is about or below 2°C (35.6°F), for each activity type below, during which time periods do you usually undertake it at home (multiple choice) and what's the frequency (per week) and duration (during each episode)?

Example: If you usually cook hot meals for 10 mins at 8 am and 25-40 mins at 7 pm every working day and you have 5 working days a week, you can enter like the example in the first row.

	How many times do you undertake the activity per week (consider only working days)	Peak hours 05:00-13:00	Peak hours 16:00-20:00	Peak hours 22:00-24:00	Other non-peak hours
	Please input the number	Typical duration(min)	Typical duration(min)	Typical duration(min)	Typical duration(min)
<u>Example 1: Cook hot meals</u>	10	10	25-40		
Cook hot meals					
Boil drinking water					
Shower					
Use a washing machine					
Work with					

electric appliances					
Leisure with electric appliances					

Q3.8 Context - No.2

For which activity type do you have a different schedule on **non-working** days



in the **cold** season ?



Please select all that apply.

- ☐ Cook hot meals
- ☐ Boil drinking water
- ☐ Shower
- ☐ Use a washing machine
- ☐ Work with electric appliances
- ☐ Leisure with electric appliances

Display This Question:

If Context - No.2 For which activity type do you have a different schedule on non-working days in... q://QID36/SelectedChoicesCount Is Greater Than 0

Carry Forward Selected Choices from "Context - No.2 For which activity type do you have a different schedule on non-working days in the cold season? Please select all that apply. "



Q3.9 Context - No.2

Your different schedules on **non-working** days



during the **cold** season



are:

Similar to Q 3.7

Q3.10 Context - No.3

For which activity type do you have a different schedule on **working** days



in the **warm** season e.g., from June to August, or the average high temperature is about or above 20°C (68°F)?



Please select all that apply.

Similar to Q 3.8

Display This Question:

If Context - No.3 For which activity type do you have a different schedule on working days in the w... q://QID112/SelectedChoicesCount Is Greater Than 0

Carry Forward Selected Choices from "Context - No.3 For which activity type do you have a different schedule on working days in the warm season e.g., from June to August, or the average high temperature is about or above 20 - C (68 - F)? Please select all that apply."



Q3.11 Context - No.3

Your different schedules on **working** days  in the **warm** season  are:

Similar to Q 3.7

Q3.12 Context - No .4

For which activity type do you have a different schedule on **non-working** days  in the **warm** season  ?

Similar to Q 3.8

Display This Question:

If Context – No .4 For which activity type do you have a different schedule on non-working days in... q://QID113/SelectedChoicesCount Is Greater Than 0

Carry Forward Selected Choices from “Context – No .4 For which activity type do you have a different schedule on non-working days in the warm season? Please select all that apply.”



Q3.13 Context – No.4

Your different schedules on **non-working** days  in the **warm** season  are:

Similar to Q 3.7

Display This Question:

If What type of electricity tariff do you have now in terms of prices during the day? = Time of Use tariffs (e.g., Economy 7): You pay different rates at different times of the day.

Q3.14 Have you ever switched from a single rate electricity tariff to a Time of Use tariff?

- ☐ Yes
- ☐ No

Display This Question:

If Have you ever switched from a single rate electricity tariff to a Time of Use tariff? = Yes

Q3.15 Have you changed your schedule of the following activities due to the electricity tariff switch?

Please select all activities and changes that apply.

	Reschedule the activity to off-peak hours	Reduce the energy intensity of activity or drop it
Cook hot meals (e.g., use electric hobs, microwave and electric oven)	☐	☐
Boil drinking water (e.g., use an electric kettle)	☐	☐
Shower (e.g., use electric showers)	☐	☐
Use a washing machine	☐	☐
Work with electric appliances(e.g., laptop)	☐	☐
Leisure with electric appliances(e.g., TV)	☐	☐

Display This Question:

If Have you changed your schedule of the following activities due to the electricity tariff switch?... [Reschedule the activity to off-peak hours] (Count) > 0

Q3.16 How did you reduce the electricity intensity of the activity or what activity did you undertake instead after dropping it?

Display This Question:

If Have you changed your schedule of the following activities due to the electricity tariff

switch?... [Reduce the energy intensity of activity or drop it] (Count) > 0

Q3.17 What did you do during the peak hours after rescheduling the activities to off-peak hours?

End of Block: Current schedule

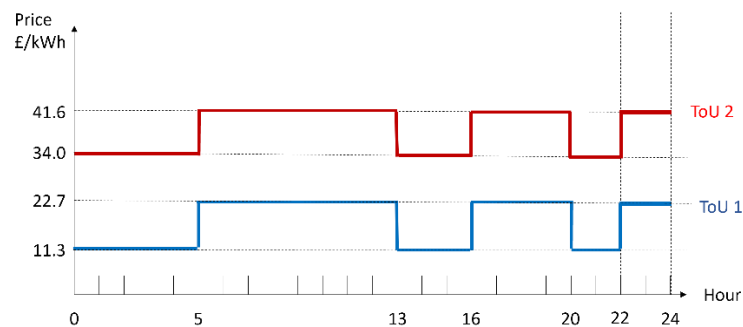
Start of Block: Intro to hypothetical situations

Q4.1 Now let's focus on a hypothetical situation when you switch from a single rate tariff to a Time of Use tariff.

Example:

Starting from 1st October 2022, the Energy Price Guarantee has raised the Electricity Price Cap from 28 pence/kWh to 34 pence/kWh. Due to the increasing single rate, you switch to a Time of Use tariff with fixed peak and off-peak hours. The peak rate is 26.4~41.6 pence/kWh and the off-peak rate is 11.3~34.0 pence/kWh (always lower than the peak rate).

The peak hours, off-peak hours and two potential Time of Use tariffs are shown below:



	Off-peak 1	Morning peak	Off-peak 2	Afternoon peak	Off-peak 3	Evening peak
Time	00:00-05:00	05:00-13:00	13:00-16:00	16:00-20:00	20:00-22:00	22:00-24:00
Example: TOU1	11.3	22.7	11.3	22.7	11.3	22.7
Example: TOU2	34.0	41.6	34.0	41.6	34.0	41.6

Unit: pence/kWh

End of Block: Intro to hypothetical situations

Start of Block: Block1_Intro_WTA_BoilDrinkingWater

Survey Flow Note: This block will be adjusted based on the activity type and measuring ways of value change, i.e., saving and payment in different blocks. The example here is boiling drinking water

Q5.1 Due to the switch of electricity tariffs, you have the possibility to change your activity schedules (or not) including:

A: Reschedule the activity from peak hours to off-peak hours

Example: change the timing of cooking a hot meal from 7 pm (peak hours) to 9 pm (off-peak hours).

B: Reduce the electricity intensity of the activity or **drop** the activity during peak hours.

Example: Use the microwave (less energy-intensive) instead of electric hobs when cooking a hot meal at 7 pm (peak hours).

Example: Order food delivery instead of cooking a hot meal

C: No change

Example: Still cooking a hot meal at 7 pm (peak hours)

Each alternative option is characterised by the following attributes:

- **The rescheduled time of activity** (if applicable): The off-peak hours you reschedule the activity **from peak hours to**.
- **The cost saving:** how much you can save by choosing the alternative

We will now present 6 scenarios for the following activity: **Boil drinking water** (e.g., use electric kettles)

After each scenario, we will also ask whether your choice will change by date or season.

Please read carefully and choose your preferred alternative.

Q5.2 This set of scenarios is about the activity $\{e://Field/Activity\}$.  .

End of Block: Block1_Intro_WTA_BoilDrinkingWater

Start of Block: Block1_SP_WTA_BoilDrinkingWater

Display This Question:

If Loop 1: 1, 41.6, 34.0, Off-peak hours, 2... Current Loop

Q6.1 Activity: $\{e://Field/Activity\}$

Scenario No. $\{lm://Field/1\}$ of 6

Context:

- **Date and season:** On a typical working day  during

the cold season  ,

- **Activity and time:** you usually undertake the

activity $\{e://Field/Activity\}$  during the $\{e://Field/Activitytime\}$.

- **Electricity tariff:** You switch to a Time of Use tariff with a peak rate of $\{lm://Field/2\}$ pence/kWh and an off-peak rate of $\{lm://Field/3\}$ pence/kWh.

Scenario:

Which of the following alternatives (A, B, C) would you choose?

Activity: $\{e://Field/Activity\}$

	A	B	C
Action	Reschedule the activity	Reduce the intensity or drop the activity	No change
Time	To $\{lm://Field/4\}$	During $\{e://Field/Activitytime\}$	During $\{e://Field/Activitytime\}$
Saving	$\{lm://Field/5\}$ £/month $\{lm://Field/6\}$ £/year	$\{lm://Field/7\}$ £/month $\{lm://Field/8\}$ £/year	0

- ☐ A
- ☐ B
- ☐ C

Display This Question:

If Loop 1: 1, 41.6, 34.0, Off-peak hours, 2... Not Current Loop

Survey Flow Note: Question 6.2 is a simplified version of Question 6.1 to avoid repetitive long sentences of contexts. Question 6.2 will be repetitively presented 5 times, resulting in 6 hypothetical tasks in total with Question 6.1.

Q6.2 Activity: $\{e://Field/Activity\}$ 

Scenario No. $\{lm://Field/1\}$ of 6

Context Summary:

Date	Season	During hours	Undertake activity	Peak price (pence/kWh)	Off-peak price (pence/kWh)
working	cold	$\{e://Field/Activitytime\}$	$\{e://Field/Activity\}$	$\{lm://Field/2\}$	$\{lm://Field/3\}$

Scenario:

Which of the following alternatives (A, B, C) would you choose?

Activity: $\{e://Field/Activity\}$

	A	B	C
Action	Reschedule the activity	Reduce the intensity or drop the activity	No change
Time	To $\{\text{Im}://\text{Field}/4\}$	During $\{\text{e}://\text{Field}/\text{Activitytime}\}$	During $\{\text{e}://\text{Field}/\text{Activitytime}\}$
Saving	$\{\text{Im}://\text{Field}/5\}$ £/month $\{\text{Im}://\text{Field}/6\}$ £/year	$\{\text{Im}://\text{Field}/7\}$ £/month $\{\text{Im}://\text{Field}/8\}$ £/year	0

- ☐ A
☐ B
☐ C

Display This Question:

If Loop 1: 0.25, 1.49, 1.49, Off-peak 2, 13... Current Loop

Q6.3 The context for the former question is

Undertake Activity: $\{\text{e}://\text{Field}/\text{Activity}\}$ on a working day in the cold season For the same question, In which of the following context you are most likely to have a different choice?

- ☐ ☒ Different date: A non-working day in the cold season
☐ ☒ Different season: A working day in the warm season
☐ ☒ Different date and season: A non-working day in the warm season

Display This Question:

If Loop 1: The context for the former question is Undertake Activity: $\{\text{e}://\text{Field}/\text{Activity}\}$ on a working day... = Different date: A non-working day in the cold season

Survey Flow Note: The context in Question 6.4 is determined by the selection in Question 6.3. Similarly, Question 6.3 will be repetitively presented 6 times to cover 6 hypothetical tasks.

Q6.4 Activity: $\{\text{e}://\text{Field}/\text{Activity}\}$



Scenario No. $\{\text{Im}://\text{Field}/1\}$ of 6

Your different choice on a **non-working** day



Context Summary:

Date	Season	During hours	Undertake activity	Peak price (pence/kWh)	Off-peak price (pence/kWh)
------	--------	--------------	--------------------	------------------------	----------------------------

non-working	cold	$\{e://Field/Activitytime\}$	$\{e://Field/Activity\}$	$\{lm://Field/2\}$	$\{lm://Field/3\}$
--------------------	------	------------------------------	--------------------------	--------------------	--------------------

	A	B	C
Action	Reschedule the activity	Reduce the intensity or drop the activity	No change
Time	To $\{lm://Field/4\}$	During $\{e://Field/Activitytime\}$	During $\{e://Field/Activitytime\}$
Saving	$\{lm://Field/5\}$ £/month $\{lm://Field/6\}$ £/year	$\{lm://Field/7\}$ £/month $\{lm://Field/8\}$ £/year	0

- ☐ A
- ☐ B
- ☐ C

End of Block: Block1_SP_WTA_BoilDrinkingWater

Start of Block: Block1_Follow up question_BoilDrinkingWater

Display This Question:

If Loop any: Activity: $\{e://Field/Activity\}$ Scenario No. $\{lm://Field/1\}$ of 6 Context: Date and season: On... = B

Or Loop any: Activity: $\{e://Field/Activity\}$ Scenario No. $\{lm://Field/1\}$ of 6 Context Summary: Date Season ... = B

Or Loop any: Activity: $\{e://Field/Activity\}$ Scenario No. $\{lm://Field/1\}$ of 6 Your different choice on a no... = B

Or Loop any: Activity: $\{e://Field/Activity\}$ Scenario No. $\{lm://Field/1\}$ of 6 Your different choice during t... = B

Or Loop any: Activity: $\{e://Field/Activity\}$ Scenario No. $\{lm://Field/1\}$ of 6 Your different choice on a non-... = B

And If

Have you changed your schedule of the following activities due to the electricity tariff switch?... != Boil drinking water (e.g., use an electric kettle) [Reduce the energy intensity of activity or drop it]

Q7.1 In the question about activity $\{e://Field/Activity\}$, you have chosen "Reduce the intensity or drop the activity" once or more.

How do you think you can reduce its electricity intensity or what activity will you undertake instead after dropping it?

Display This Question:

If Loop any: Activity: \${e://Field/Activity} Scenario No. \${lm://Field/1} of 6 Context: Date and season: On... = A

Or Loop any: Activity: \${e://Field/Activity} Scenario No. \${lm://Field/1} of 6 Context Summary: Date Season ... = A

Or Loop any: Activity: \${e://Field/Activity} Scenario No. \${lm://Field/1} of 6 Your different choice on a no... = A

Or Loop any: Activity: \${e://Field/Activity} Scenario No. \${lm://Field/1} of 6 Your different choice during t... = A

Or Loop any: Activity: \${e://Field/Activity} Scenario No. \${lm://Field/1} of 6 Your different

choice on a non-... = A

And If

Have you changed your schedule of the following activities due to the electricity tariff switch?... != Boil drinking water (e.g., use an electric kettle) [Reschedule the activity to off-peak hours]

Q7.2 In the question about activity **\${e://Field/Activity}**, you have chosen "Reschedule the activity" once or more.

What activity will you undertake during the **\${e://Field/Activitytime}** after the rescheduling?

End of Block: Block1_Follow up question_BoilDrinkingWater

Start of Block: Block1_Choice bias_WTA_BoilDrinkingWater

Q8.1 Are there any alternatives presented in the choice exercises that you would never consider? Please select all that apply.

- ☐ Reschedule the activity
- ☐ Reduce the intensity or drop the activity
- ☐ No change

Q8.2 Did you disregard any of the attributes presented in the choice exercises? Please select all that apply.

- ☐ The new time of rescheduled activities (if applicable)
- ☐ The cost saving

End of Block: Block1_Choice bias_WTA_BoilDrinkingWater

Start of Block: Block1_Bound_WTA_BoilDrinkingWater

Q9.1 How much **saving per day/month/year** would lead you to consider changing this activity(e.g., rescheduling or reducing the electricity intensity)? Please indicate an amount in £.

Please leave the box blank If you would not consider rescheduling the activity whatever the saving.

	Unit			when the saving is beyond...
	per day	Or per month	Or per year	
I would consider changing the activity \${e://Field/Activity1}	☐	☐	☐	

End of Block: Block1_Bound_WTA_BoilDrinkingWater

Start of Block: Block7_Intro_Threshold_BoilDrinkingWater

Survey Flow Note: This shows how the other measuring way of value change is expressed: Payment. The following questions related to this activity are similar to questions in Block 6 and thus are not presented here.

Q10.1

Due to the switch of electricity tariffs, you have the possibility to change your activity schedules (or not) including:

- **A: Reschedule** the activity from peak hours to off-peak hours
 - Example: change the timing of cooking a hot meal from 7 pm (peak hours) to 9 pm (off-peak hours).
- **B: Reduce** the electricity intensity of the activity or **drop** the activity during peak hours.
 - Example: Use the microwave(less energy-intensive) instead of electric hobs when cooking a hot meal at 7 pm (peak hours).
 - Example: Order food delivery instead of cooking a hot meal
- **C: No change**
 - Example: Still cooking a hot meal at 7 pm (peak hours)

Each alternative option is characterised by the following attributes:

- **The rescheduled time of activity** (if applicable): The off-peak hours you reschedule the activity from peak hours to.
- **The cost:** how much you will pay for the electricity consumed by the activity.
 - Note: This cost can be 0 when the activity is dropped or consumes no electricity (Alternative B).

We will now present 6 scenarios for the following activity:

- **Boil drinking water** (e.g., use electric kettles)

After each scenario, we will also ask whether your choice will change by date or season.

Please read carefully and choose your preferred alternative.

Start of Block: Personal information

Q65.1 At last, we need to know a little bit more about you.

Q65.2 What is your gender?

- ☐ Male
- ☐ Female
- ☐ Prefer another term:

-
- ☐ Prefer not to answer

Q65.3 Whereabouts in the UK do you live? Please type in the name of your city, such as London or Edinburgh.

Q65.4 What best describes your employment status over the last three months?

- ☐ Working full-time
- ☐ Working part-time
- ☐ Unemployed and looking for work
- ☐ A homemaker or stay-at-home parent
- ☐ Student
- ☐ Retired
- ☐ Other

Q65.5 How many working days do you have from home and away from home in a week (7 days)?

	Click to write Column 2
--	-------------------------

	Number of days in a week
Working away from home	
Working from home	

Q65.6 How many people are living in the same property with you (excluding yourself)?

	Number			
	0	1	2	3 or more
Children (from 0 to 12 years old)	☐	☐	☐	☐
Children (from 13 to 17 years old)	☐	☐	☐	☐
Adult (from 18 to 60 years old)	☐	☐	☐	☐
Older adult (60 years old and above)	☐	☐	☐	☐

Q65.7 What is your annual household income (before tax)?

- ☐ Less than £20,000
- ☐ £20,000 - £40,000
- ☐ £40,000 - £60,000
- ☐ £60,000 – £80,000
- ☐ £80,000 - £100,000
- ☐ £100,000 or more
- ☐ Prefer not to answer

Q65.8 What type of property do you live in?

- ☐ Flat or apartment
- ☐ Semi-detached house or terraced house

- ☐ Detached house, cottage or bungalow
- ☐ Other, please specify:

Q65.9 Which option best describes who owns the property that you live in?

- ☐ Owned by yourself, partly or wholly
- ☐ Owned by another family member(s) or relatives
- ☐ Rented
- ☐ Other, e.g., school/company dormitory, home-stay. Please specify:

Q65.10 What products do you have or are equipped in the property that you live in? Please select all that apply.

- ☐ Electric car
- ☐ Electric scooter
- ☐ Renewable energy generators (e.g., solar panels)
- ☐ Energy storage systems (e.g., home battery)
- ☐ Smart meter

Q65.11 How much do you agree with the following statements?

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
I am aware of the impact of the way I use electricity at home on the <u>environment</u> .	☐	☐	☐	☐	☐
I am aware of the impact of the way I use electricity at home on <u>society</u> .	☐	☐	☐	☐	☐
I am aware of the impact of the way I use electricity at home on my <u>electricity bill</u> .	☐	☐	☐	☐	☐

Q65.12 How much do you agree with the following statements?

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The impact of my household activity on the <u>environment</u> plays a big part in my activity scheduling decisions.	☐	☐	☐	☐	☐
The impact of my household activity on <u>society</u> plays a big part in my activity scheduling decisions.	☐	☐	☐	☐	☐
The impact of my household activity on my <u>electricity bill</u> plays a big part in my activity scheduling decisions.	☐	☐	☐	☐	☐

Q65.13 How much do you agree with the following statements?

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
A Time of Use tariff will make the environment and society more sustainable.	☐	☐	☐	☐	☐
You will save money with a Time of Use tariff compared with a single rate tariff by rescheduling activities.	☐	☐	☐	☐	☐
You prefer a Time of Use tariff to a	☐	☐	☐	☐	☐

single rate tariff.					
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Q65.14 If you have any comments regarding your responses or this survey in general, please use the entry box below:

Best regards,
Han Wang

Research Postgraduate
Department of Civil and Environmental Engineering
Imperial College London

End of Block: Personal information
