A Generalised Model for Assessing the Large-scale Deployment of Residential Energy Management Systems

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Abstract

Residential energy management systems are a class of devices that can provide demand side electricity management capabilities for residential customers and retailers. As such, they have the potential to provide financial benefits for customers, retailers and the electricity market. Nevertheless, a poor articulation of the cost and benefits of these devices has limited their widespread use and stunted their possible contributions to an efficient grid system. This situation stems, in part, from an inability to adequately model and measure the performance of these devices on a large-scale. Current modelling techniques heavily rely on disaggregated appliance data from households. As such, data is not available in large quantities (for several thousand households). Moreover, current modelling techniques fail to consider the customer's baseline load profile (the load profile the customer is expected to have if the customer they are not participating in a demand response program) that is used to measure the performance of these devices, and often employ suboptimal customer baseline load profiles to calculate a device's demand response.

To address these issues, this thesis was dedicated to developing a generalised model of a residential energy management system that uses household aggregated load profile data and that optimally selects a customer baseline load profile to model the behaviour of these devices. The generalised residential energy management system model was based on an Autoregressive Integrated Moving Average (ARIMA) model that was modified to reflect the forecast reductions in average, and peak to average, demand that is produced by these devices during demand response. The generalised model was validated and used to conduct a full factorial analysis to examine how socio-demographic profile, tariff structures, and the choice of operational objectives of these devices, interact to influence their benefits and costs for

customers. Once this was understood, the concepts of social welfare maximisation and customer baseline load profile accuracy was used to fit the generalised model with a procedure for optimally selecting a customer baseline load profile to measure the devices' demand response performance.

Several key results were obtained in the process of creating the generalised model. It was shown that the demand response benefits, and cost derived from these devices, depend on the specific combination of customer socio-demographics, tariff type, and operational objectives used by these devices. It was shown that if a uniform set of objectives is used for residential energy management systems, when these devices are mass deployed, this would lead to an unequal distribution of benefits for customers.

It was also shown that residential energy management systems can influence retail risk by directly reducing variation in residential demand and indirectly influencing the relationship between customer diversity and variation in aggregated electricity demand. In addition, it was demonstrated that if a single customer baseline load profile is used to measure demand response across different customers this leads to a loss in economic advantage for some customers. If, however, these customer baseline load profiles were customised for individual customers based on demographics and tariff paid, and these customer baseline load profiles were later aggregated to measure the demand response of a customer group, this would ensure both local and global maximisation of social welfare for the customers and retailer.

In summary the generalised model developed provided key insights into the influence that these systems can have once deployed on a large scale. The key findings of the research not only contributed to the current state-of-the-art but also provided avenues for substantial future research.

Attestation of Authorship

I hereby declare that the content of this work is original, except where specific reference is made to the work of others. I also declare that this work has not been submitted in whole or in part for the award of any other degree or qualification to any other university or institution of higher learning.

Peter Jean Paul

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Nomenclature

Acronym	Description
α_n	Regression coefficients of past average electricity use values (A_{t-n})
$A(j)$	Incentive received by customer for reducing demand during period j
A_{t-n}	Past average electricity use values n time steps behind
ARIMA	Autoregressive integrated moving average
β_1	Weights indicating importance of customer to demand response program
β_2	Weights indicating importance of retailer to demand response program
b_c	Residential energy management system objective and cost-benefit ratio for customer
β_n	Regression coefficients of past average-to-peak electricity use values (Q_{t-n})
B_t	Hourly base load
c	Social cost of one kilogram of CO_2 emissions
c_r	Kilograms of CO_2 emissions per kilowatt hour of electricity demand
ΔC_D	Change in retail cost as a result of the reduction in electricity use of the customer
C_p	Cost price of the residential energy management system
δ	Correction factor for the units of simple payback period
∂d	Difference in demand between two periods
$\partial \rho$	Difference in price between two periods
d_0	Initial demand within a certain period
d_a	Electricity demand during period "a"
d_b	Electricity demand during period "b"
d_t	Electricity use value to be forecast
d_t^*	Reduced electricity demand during hour "*t*"
d_{t-n}	Past hourly electricity use "*n*" time steps behind

Acronym	Description
$[d_t]_m$	Vector containing hourly energy use data for the average monthly load profile
D^*	Total reduced electricity demand
D_t	Aggregated hourly demand
E_A	Economic advantage of selecting a baseline to measure the performance of a group of residential energy management systems
$E(i,i)$	Self-elasticity of customer participating in demand response program within period "i"
$E(i,j)$	Cross elasticity between period "i" and "j" of customer participating in demand response program
e_{t-m}	Past hourly forecasted errors
f^2	Effect size metric measuring the effect of customer diversity on variance in aggregated demand
J_1	Objective function for energy savings obtained from device
J_2	Objective function for emissions savings obtained from device
J_3	Objective function for tax savings obtained from device
J_4	Objective function for retail portfolio savings obtained from device
J_5	Objective function for customer discomfort obtained from device
J_6	Objective function for payback period obtained from device
k	The number of customer sets used to establish the relationship between customer diversity and variance in aggregated demand
k_1	Percentage in average electricity use remaining after demand response by residential energy management system
k_2	Percentage in peak-to-average electricity use remaining after demand response by residential energy management system
$\hat{L}$	Likelihood function.

Acronym	Description
μ	Root-mean-square of errors
μ_p	Average profit earned by a retail portfolio
$\Delta\mu_p$	Change in average profit earned by a retail portfolio
μ_{p_2}	Final profit in portfolio after residential energy management systems have been deployed
μ_{p_1}	Initial profit in portfolio before residential energy management systems have been deployed
μ_{σ_1}	Average variance of demand of the households before the deployment of residential energy management systems
μ_{σ_2}	Average variance of demand of the households after the deployment of residential energy management systems
n	Number of data points used to calculate the model.
N	Total number of households in demand response program
N_m	Noise associated with human activity within the household
p	Number of past electricity use values needed in autoregressive integrated moving average model
P_m	Profit made by the retailer from electricity consumed by households
ρ_0	Initial tariff paid by a customer within a given hour
$pen(j)$	Penalty for not reducing demand during period j
p_p	Simple payback period; length of time required to fully pay for the device
φ_n	Regression coefficients for demand terms in autoregressive integrated moving average model
q	Past forecasted error values needed in autoregressive integrated moving average model
Q_{t-n}	Past average-to-peak electricity use values for household

Acronym	Description
ΔR_D	Change in revenue for the retailer as a result of the reduction in electricity consumption
r_t	Hourly retail tariff paid by residential customer
ρ^2	Correlation between customer diversity and variance in aggregated demand
S_i	Customer diversity during hour "i"
s_h	Demand of household "h" during hour "i"
s_N	Aggregated demand of households during hour "i"
s_t	Hourly spot price
θ_m	Regression coefficients for error terms in autoregressive integrated moving average model
τ	Original tax on electricity bill
$\tilde{\tau}$	Reduced tax on electricity bill
t	Number of hours in forecast horizon used for autoregressive integrated moving average model
σ_1	Standard deviation of aggregated demand of households before the deployment of residential energy management systems
σ_2	Standard deviation of aggregated demand of households after the deployment of residential energy management systems
${\sigma_\varepsilon}^2$	Variance in the root-mean-square errors of the model
${\sigma^2}_p$	Variance in profit for retail portfolio
$\Delta{\sigma^2}_p$	Change in variance of profit earned by retail portfolio
${\sigma^2}_t$	Variance in household load profile before installing device
${{\sigma^2}_t}^*$	Variance in household load profile after installing device
$[\sigma_t]_m$	Vector containing hourly standard deviation of electricity demand data for the average monthly load profile
U	Total social welfare from the demand response program

Acronym	Description
w_1	Weight for energy savings objective function
w_2	Weight for emissions savings objective function
w_3	Weight for tax savings objective function
w_4	Weight for retail portfolio savings objective function
w_5	Weight for customer discomfort objective function
w_6	Weight for payback period objective function
x_e	Errors produced by the model
Y_n	Numerator of residential energy management system objective function
${Y_n}'$	First derivative of numerator of residential energy management system objective function
${Y_n}''$	Second derivative of numerator of residential energy management system objective function
Y_d	Denominator of residential energy management system objective function
${Y_d}'$	First derivative of denominator of residential energy management system objective function
${Y_d}''$	Second derivative of denominator of residential energy management system objective function

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Chapter 1

Introduction

1.1 Research background

An increase in electricity consumption has led to a need to increase electricity supply [1]. However, it is recognised that increasing electricity supply has a negative environmental impact particularly with regard to increased CO_2 emissions and climate change [2]. In this context renewable energy sources and infrastructure are also becoming important; however, finding optimal sites to install large scale renewable sources such as hydro-dams has been difficult [3]. These issues have combined to make it challenging to expand the electricity grid.

In light of these challenges, many academics and industry stakeholders have advocated upgrading the grid with smart technologies to create a smart grid [4]. A smart grid measures and manages electricity (and more broadly energy) to make more efficient use of limited energy resources [4]. Smart technologies include smarter meters, sensors, smart appliances and two-way communication channels to enable exchange of information from the customer to the retailer [4].

This smart grid is meant to provide more efficient use of the grid, in part, by providing a higher degree of demand side management. Demand side management includes all activities or programs undertaken by load-serving entities or their customers to manage a site's energy consumption by load management and control with the aim of cost and efficiency optimization [5]. One of the most effective techniques for demand side management is demand response [6].

Demand response is the deliberate modification of electricity use of consumers to reduce or shift total electricity consumption [7]. Programs are often created where customers sign up and agree to provide load modification capabilities to the utility. These are called demand response programs which fall under two general categories: incentive based and price-based demand response programs [8]. It has been generally recognised that, whilst customers are willing to change their energy consumption to benefit the environment and society, customers do not want to spend time analysing and making electricity consumption decisions and micro-managing electricity loads at their premises [9]. For this reason, energy management systems were developed [9].

An energy management system consists of computer aided devices that are used at various levels of the grid to monitor, control, and optimise the performance of electricity production and consumption [10]. In the past these devices have been primarily used by grid operators, and industrial and commercial customers [11]. Recently, because residential customers have become more conscious of electricity prices and the social and environmental impact of their electricity use, residential energy management systems have come to the fore as being a potential tool to help residential customers to reduce their electricity use [12]. Studies have shown that residential energy management systems are potentially the most versatile demand response tools to date [13]. The global market for these devices is expected to reach $62.3 billion by 2023 with a growth rate of 3.5% forecast during the period 2017 to 2023 [14].

With regard to these devices, previous literature has concentrated on methods for modelling their operation usually involving single households or a small group of households [15]. Some areas of research include developing optimization methods such as predictive and heuristic control algorithms for creating efficient operation schedules and making good consumption and production decisions [15]; other areas of research revolve around communication protocols between these systems and household appliances and communication protocols between customer and electricity retailer [16]. Whilst past research has provided a solid foundation for establishing potential benefits, the benefits shown in small scale studies do not necessarily translate to the same benefits when these devices are installed on a large scale. In fact, there are still several issues that hinder any substantial investigation into the potential large-scale benefits that customers and retailers can realise from these devices [17].

1.2 Problem description and significance of study

The typical techniques used to model these devices rely heavily on disaggregated appliance data in order to create optimal schedules for household loads to curtail or shift the electricity use and determine the optimal demand response that a customer can provide [18]. However, large quantities of disaggregated electricity use data (from several thousand households) is not readily available [19]. Whilst some researchers attempt to overcome that problem by providing mathematical models for appliances [20], the diversity of appliances alone makes it difficult to apply these models generally and obtain reasonable results in terms of the optimal demand response a customer can provide. This has limited the scope and depth of research that can be done on residential energy management systems.

Research has shown that these devices can reduce electricity use of the household, with several papers quoting the percentage reduction that can be obtained. Nevertheless, since past research papers have mainly focused on small scale studies of different customers, tariff types and operational objectives when modelling these devices [21], it is difficult to determine the conditions that would produce an optimal demand response for a given customer [21]. This has resulted in uncertainty in determining the cost benefit of these devices for a given customer. This has also translated into uncertainty in determining the overall impact that these devices can have on the retail portfolio of an electricity provider; some research articles claim that these devices can reduce retailer profit whilst others suggest an improved profit [22].

Compounding these issues is the fact that there has been very little research investigating how demand response customer baseline load profiles are selected to measure the amount of demand response provided by these devices. Customer baseline load profiles (or baselines) reflect the load profile customers are expected to ordinarily have if they were not participating in a demand response program. In fact, most research papers reviewed simply measure the demand response produced by these devices as the difference between the load profile produced by the devices and the historical load profile of the household. Whilst this appears to be a common feature in existing literature [23], research on demand response programs has indicated that historical data is not necessarily the best customer baseline load profile to measure the demand response provided by smart technology [24]. Consequently, the current state-of-the-art does not have a great degree of research addressing methods to optimally select a customer baseline load profile to measure the demand response of residential energy management systems [24]. Nevertheless, baselines are highly important for economic feasibility studies, market research, cost-benefit analysis and measuring demand response; having an optimal customer baseline load profile for such economic activities is essential.

The issues associated with these devices can be classified into two broad categories: a poor articulation of the cost and benefits of these devices stemming from an inability to adequately model and assess their performance on a large-scale; and, very little consideration of the baseline used to measure their performance.

Having a clear modelling approach that can be used for the large-scale study of residential energy management systems has several advantages. Modelling can avoid unnecessary resource-intensive economic feasibility studies that are commonly undertaken to examine possible smart grid advances. This would aid in decision making process in terms of deciding whether a capital investment in these devices is advantageous. This in turn would help prioritise investments particularly where there are other demand response options available. A generalised model for residential energy management systems also provides a benchmark for comparing large-scale demand response projects. Such a model could provide a standard from which different customer marketing initiatives for these systems can be compared and determine which one would yield the greatest return. A generalised model would make it possible to quantify the effects that a change initiative can have on different grid stakeholders.

Furthermore, having a model that can select an optimal baseline to measure its demand response is critically significant for a demand response program. Optimal customer baseline load profile for customer renumeration for participation in demand response programs could be accurately calculated so that customers are not under- or over-compensated. This is particularly useful for incentive-based demand response programs. Moreover, having an optimal baseline to measure demand response is particularly useful in cases where the retailer would choose to make demand response from residential customers a significant part of their electricity portfolio. In such a case, the accuracy of a baseline would become important for situations such as portfolio hedging and market bidding.

1.3 Research aim and objectives

Considering the potential importance of residential energy management systems, it is worth investigating the issues mentioned and providing possible solutions to these issues. Therefore, the overarching aim of this work was:

> ***To develop a generalised model of a residential energy management system that uses household aggregated load profile data and that optimally selects a baseline to model the behavior of these devices.***

To achieve the aim the following objectives were set out:

1. Design a generalised model of a residential energy management system capable of modelling load reduction and load shifting without the need for disaggregated appliance data.

2. Use the generalised residential energy management system model to examine how customer socio-demographic profiles, tariff structures, and the choice of operational objectives of these systems, interact to influence their benefits and costs for customers and retailers.
3. Create a method using the concepts of social welfare maximization and baseline accuracy for optimally selecting an appropriate baseline to measure the demand response of residential energy management systems.

1.4 Major contributions of this work

Through achieving the objectives set out for this work and fulfilling the overall goal of the thesis, the following major contributions were made to the state-of-the-art:

A validated generalised model for a residential energy management system was developed using a time series model called an Autoregressive Integrated Moving Average (ARIMA) model. This generalised residential energy management system model uses the load profile of a household to forecast the optimal demand response that can be achieved by a customer. The model is also capable of measuring the monetary benefits that the device provides for the customer during the forecast period using a cost-benefit metric (b_c). The metric itself is constructed by combining six of the most common objective functions for residential energy management systems found in literature. Four out of these six functions represent the benefit the device provides to the customer (electricity bill savings, emissions savings, tax savings and increase in retail profit) and the other two, the cost to the customer of the device (discomfort and a simple payback period associated with the device).

Given the generalizability of the model, it was used to conduct a cost-benefit analysis for the customer and the retailer in a scenario where the devices are installed on a large scale in the 5,379 households that participated in the Low Carbon London project. The second major contribution of this work was to show that the demand response that is provided by these devices is affected by the customer socio-demographic profile, tariff type and the operational objectives used to operate the device. Every customer has an optimal set of objectives that maximises the benefits that the customer receives from the device and maximises the demand response that a customer can provide. Many published papers have not considered that possibility of customers having an optimal set of objectives to maximise their demand response.

Based on the cost-benefit analysis, another major contribution was made with the discovery that, depending on the set of operational objectives used to operate these devices, residential energy management systems can both increase and decrease the profit made by an electricity retailer. Furthermore, these devices have both a direct impact on the risk experienced by a retailer (by reducing the variance in electricity use from households) and an indirect impact by influencing the relationship between customer diversity and retail risk. Ordinarily it is assumed that customer diversity reduces retail risk. However, with the introduction of these systems, this thesis has shown that these devices can strengthen or weaken the effect of customer diversity on risk. This is a major contribution since hitherto there has been very little work examining both the direct and indirect effects of these devices on retail portfolios.

Using the concepts of social welfare maximization, baseline accuracy-bias trade-off, and the cost benefit analysis done on these devices, a general economic model has been created to optimally select a baseline of measure the demand response of residential energy management systems. In the process of creating this model, a cost-benefit metric was developed for the retailer based on the change in profits that they experience and the correlation between customer diversity and retail portfolio risk. Very little work has been done on such a model and, as such, this model is a major contribution of this work. With this model, the collective economic advantage of using a baseline was quantified. Based on this quantification it was clear that using a single baseline to measure the demand response of all customers would lead to a loss of social and economic welfare for both the customer and retailer. Instead it was demonstrated that using customised baselines for different customer groups ensured both local maximization of benefits for the customer and a global maximization of benefits for the retailer.

Because of the significance of the contributions made in this work, parts of this thesis were condensed and submitted for journal publication with the following articles being successfully published:

- Jean-Paul, Peter, Tek-Tjing Lie, Timothy N. Anderson, and Brice Vallès. "The effect of sociodemographic diversity of residential customers on the financial risk experienced in the retail electricity market." *International Journal of Energy Research*.
- Jean-Paul, P. (2019, August). Investigating the value proposition of Energy Saving Devices. Paper presented at the Auckland University of Technology 3-Minute Thesis Finals, Auckland, New Zealand.
- Jean-Paul, Peter, Tek-Tjing Lie, Timothy N. Anderson, and Brice Vallès. "The impact of residential energy management systems on electricity retail portfolios" Proceedings of the 2020 International Conference on Smart Grids and Energy Systems (SGES 2020).

The rest of this thesis is devoted to providing a detailed explanation of how objectives were achieved and how this in turn gave rise to the development of the major contributions outlined in this chapter. Moving forward, Chapter 2 provides an overview of existing literature focusing on the versatility of residential energy management systems, the technical challenges of modelling such devices and the approaches to address these challenges.

Chapter 3 provides a novel design of a generalised model of a residential energy management system capable of modelling load reduction and load shifting without the need for disaggregated appliance data. The model uses a time series autoregressive integrated moving average technique to forecast demand response and show the influence of tariff structure, sociodemographic profile of customers and the choice of operational objectives of these devices on the demand response of customers.

In Chapter 4, the generalised residential energy management system model was used to examine how customer socio-demographic profiles, tariff structures, and the choice of operational objectives of these systems, interact to influence their benefits and costs for customers and retailers. The chapter employs actual data from UK network for demonstrating the impact of the proposed model for the customer and retailer.

In Chapter 5, a method was created using the concepts of social welfare maximization and baseline accuracy for optimally selecting an appropriate baseline to measure the demand response of residential energy management systems. Discussions are also added that demonstrate the performance of the employed optimization technique such as iteration convergence.

Chapter 6 summarises all the major findings of the thesis and outcomes of the carried-out research. The chapter also provides recommendations for future research.

Chapter 2

Literature Review

2.1 Introduction

It was established in the previous chapter that the core issue to be addressed was a poor articulation of the cost and benefits of residential energy management systems stemming from an inability to adequately model and assess their performance on a large-scale; and, little consideration of the baseline used to measure the performance of these devices. Any methods or techniques used to address these issues has to be grounded and as such should be developed from what is already known about these devices. Using this approach requires a content analysis of some of the pertinent literature that exist in the field with the specific aim of understanding what residential energy management systems are, how the aforementioned issues arose from previous attempts to model these devices and possible solutions to addressing these issues.

2.2 Versatility of residential energy management systems

Residential energy management systems are demand response tools that shift, and curtail, demand to improve the energy consumption and production profile of a dwelling on behalf of a consumer [25]. A simple categorization of these devices and how they are used to help to improve energy consumption is provided in [26]. This categorization along with some examples of these devices is shown in Table 2.1.

Table 2.1 Categories of residential energy management systems

Product Category	Information Provided by device	Control Provided by device	Examples
Load Monitors	Real time feedback on power and energy	None. Mainly used for monitoring electricity consumption	
In home display devices	Feedback on power and energy and prompts for demand response events and tariff signals	None. Mainly used for monitoring electricity consumption	
Smart Thermostat	Feedback on Heating, ventilation, and air conditioning conditions	Provides control through internet or other customer portals. Uses rule based control and machine learning	
Smart light	Feedback on status of lights	Same as Smart Thermostat	
Smart plug/switch	Feedback on the power use of appliances and status of plugs	Same as Smart Thermostat	

Table 2.1 continued…

Product Category	Information Provided by device	Control Provided by device	Examples
Smart appliances	Appliance power and use time status	Same as Smart Thermostat	
Hybrid hubs	Combined information from all other residential energy management systems	Same as Smart Thermostat	

These devices are some of the most versatile technologies for implementing demand response amongst residential customers participating in demand response programs. According to the state-of-the-art, demand response programs can be divided into 12 types [6]. Research showing the use of residential energy management systems in each of these program types is given in Table 2.2.

Table 2.2. Demand Response and versatility of residential energy management systems

Demand Response Categories	Demand Response Program Types	Residential Energy Management Systems Reference
Time-base Programs	Time-Of-Use (TOU)	[10, 27]
	Real Time Pricing (RTP)	[28, 29]
	Critical Peak Pricing (CPP)	[30, 31]
	Real time Rebate (RTR)	[25]
Incentive-based Programs	Direct Load Control (DLC)	[32]
	Interruptible Load (I/C)	[32]
	Demand Bidding (DB)	[33]
	Emergency Demand Response	[34]
	Capacity Market Program (CMP)	-
	Ancillary Service Market (ASM)	-
Energy Saving Behaviour	Process Investor Behaviour	-
	Curtailment Behaviour	[35]

It is clear from Table 2.2, that the use of residential energy management systems spans almost every area of research regarding demand response; this is a testament of the device's versatility. These devices have been shown to reduce peak-to-average electricity demand for customers paying real time pricing for their electricity use [36]. Other articles show the use of these devices in scheduling appliances to take advantage of low rates during for Time-Of-Use pricing [12].

However, it must be noted from Table 2.2 that there are areas in the current state-of-the-art that have had very little research done regarding residential energy management systems. These areas of research usually involve large scale modelling of demand response within the electricity grid; for example, Capacity Market Programs [37], Ancillary Service Market [37], and Process Investor Behaviour [38]. This illustrates some of the fundamental challenges associated residential energy management system research.

2.3 Challenges associated with modelling these devices

2.3.1 Inadequate modelling approach for large-scale studies

Previous literature [10, 39] has suggested that a typical model of a residential energy management system consists of any combination of the following: a power source (such as solar PV) and energy storage data [40]; energy consumption data of appliances generally obtained from smart meters or sensors, flexible load (example electric vehicles, water heaters) [41]; other sources of data including weather conditions such as temperature or rainfall, tariff data such as Time-of-Use and Flat rate tariffs [42]; objective functions for the system, constraints and a control system with a scheduling algorithm for the system [43]. The relationship between these individual parts is shown in Figure 2.1.

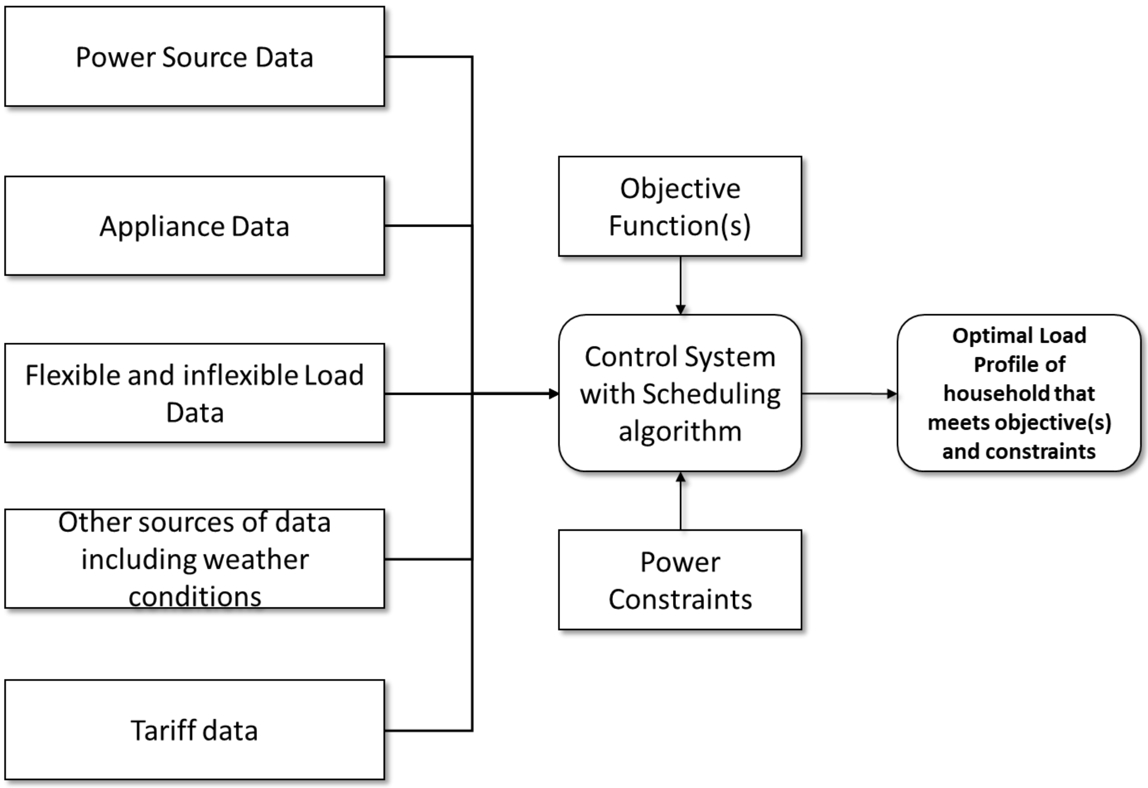


Figure 2.1. Typical components of a residential energy management system model

Control systems are generally computerised systems that use predictive [44] or heuristic [45] control algorithms to schedule the operating times of appliances that help fulfil the operational objective of the device for a given set of constraints. The result is an optimal load profile for the household [46]. For example, comparing control systems made from neural networks and support vector machines to show how the implementation of a control system can influence the residential energy management system's ability to reduce power consumption in the electricity grid [47]. Or the use of fuzzy logic control system to produce energy reductions in the household in the presence of various forms of uncertainty [48].

Table 2.3 below provides some other examples of various versions of the above model and references to research that have made use of them to do analysis in their work.

Table 2.3. Typical components used to model residential energy management systems

Components used systems	Control Algorithm	Objective functions	Constraints	References
• Household appliance data • Battery • PV	• Mixed Integer Linear Programming	• Minimise electricity use costs • Minimise waiting time	• Energy balance	[49]
• Household appliance data • Battery • Photovoltaics	• Convex programming	• Minimise electricity bill	• Battery Price • Electric grid • Capacity constraints	[50]
• Household appliance data • Battery • Photovoltaics	• Mixed-Integer Non-Linear Programming	• Minimise bill	• Energy Balance	[51]
• Household appliance data • Battery • Electricity Grid	• Genetic Algorithm • Binary Particle Swarm Algorithm	• Minimise electricity bill	• Battery Price • Capacity constraints	[52]
• Household appliance data • Battery • Electric Water Heater • Photovoltaics	• Stochastic Optimization	• Maximises customer's profit	• Performance characteristics • Response Fatigue Index • Energy balance	[53]
• Household appliance data	• Non-dominated Sorting Genetic Algorithm II	• Minimise electricity use costs • Minimise customer inconvenience	• Load levels • Ramp limits • Daily electricity use limits	[54]
• Household appliance data • Battery • Photovoltaics • Electric Vehicles	• Convex programming	• Minimise electricity bill	• Energy balance • Battery Price • Control modes of EVs	[55]

Whilst the modelling approach is good and has been used for many small-scale studies, the approach heavily relies on disaggregated electricity consumption data for household appliances [56] as can be seen from the first column of Table 2.3. Moreover, databases such as UKDALE [57] readily provide disaggregated household data for a few households, however, it is argued that there has not been, in recent times, large scale surveys (involving several thousand households) to capture such disaggregated data [57]. A quick inspection of some of the most common databases used to procure disaggregated data as shown in Table 2.4 [19, 58] provides evidence of this.

Table 2.4. Public datasets with non-intrusive disaggregated appliance data [19]

Dataset	Number of Households	Sampling Resolution	Duration	Access Rights
AMPds	19	1 min.	Apr. 2012 – Mar. 2013	Free
BERDS	1	20 sec.	Jan. 2012 – Jan. 1st 2013	Free
BLOND	1	50 kHz	Oct. 2016 – May 2017	Free
BLUED	1	12 kHz	Aug. 2012	Free
COOLL	Done in lab.	100 kHz	Jun. 2016	Free
Dataport	669	1 min.	Jan. 2011 (on going)	Free
DRED	1	From 1 kHz to 1 Hour	Jul. – Dec. 2015	Free
ECO	6	1 Hz	Jun. 2012 – Jan. 2013	Free
GREEND	9	1 sec.	1 year	Free
HES	255	10 mins.	Apr. 2010 – Apr. 2011	Require access rights
iAWE	33	1 min.	Summer of 2013	Free
PowerCon	3	1 min.	Dec. 2006 – Nov. 2010	Free
REDD	6	4 sec.	June 2011	Free for limited time
REFIT	20	8 sec.	Oct 2013 – Jun 2015	Free
Smart Home Dataset	7	NA	2014 – 2016	Free
Tracebase	> 10	1 min.	2012 – 2013	Password required
UK-DALE	5	1 sec. and 6 sec.	2012 – 2014	Free

In fact, based on the data in Table 2.4, to date one of the largest surveys done to capture disaggregated household appliance data is the Dataport Survey involving only 699 households [58]. The limited amount of appliance data has restricted the scale and depth of analysis that can be done on the operation of residential energy management systems [59, 60].

2.3.2 Cost-benefit for the customer not clearly articulated

As one would expect, different customers perceive value differently and therefore will have different expectations of energy management systems [61]. It has been noted in previous literature that socio-demographic characteristics [62] and tariff rates paid by customers [63] are two factors that influence energy use, energy management behaviour and the effectiveness of residential energy management systems. For example, [64] used 228 households (78 on Realtime-pricing and 150 on Time-Of-Use) to show that, based on customer demographics and tariff design, not every energy management system was effective for the overall welfare of customer. The authors highlighted that there needs to be an appropriate fit between customer, tariff and device design to maximise the overall welfare derived from these devices.

Similarly, in [65] a questionnaire survey of 1913 residents in China was conducted and found that that differences in socio-demographic factors such as gender, age and education all play a role in determining if residents would adopt energy management systems, and how customers would make use of these devices. Unfortunately, few attempts have been made to quantify the monetary benefits and cost that customers derive from these residential energy management systems as a result of the social differences and tariff design.

The fact that there are socially distinct groups of residential customers under different tariff regimes led to some confusion as to which operational objectives is best suited of modelling energy management systems when considering different customers [3]. For example, 298 research papers that highlighted at least 10 different objectives being used to model residential energy management systems were examined [66]. The objectives collated during the author's investigation into the state-of-the-art include: maximising energy bill and emissions saving [67], and minimizing device payback period and customer discomfort [66]. Other general objectives, such as maximising tax savings [68] and improving retailer profit [69], are also recorded in literature. Whilst small scale studies do show how individual objectives provide benefit for customers, research outlining which objective is best suited for a customer or customer group is scant.

2.3.3 Cost-benefit for the retailer not clearly articulated

Absence of large stores of appliance data has also precipitated the inability to determine the large-scale impact of these devices on retail profit. Since the role of energy management devices is to reduce electricity use and improve efficiency of households, some authors suggest that the large-scale deployment of these systems will result in a loss of retail profit [70]. Other papers [22, 71] contest this idea by advocating that demand response devices can decrease electricity cost at a faster rate than revenue (thus increasing profit) depending on how these device schedule electricity use within the household.

Retail profit, however, is only one of the metrics used to measure the possible impact that demand response technologies can have on the financial performance of the retailer. Another important metric is the financial risk experienced by the retailer. One source of financial risk is the quantity risk [72] from the variation in aggregated electricity use amongst residential customers [73] who can account for as much as 50% of retail electricity consumption [74].

Several articles have explored factors amongst these customers that may influence quantity risk; for example temperature [75], humidity [75] and the physical dwelling of customers[76]. One risk factor that has received little attention, when looking at the ability of residential energy management systems to mitigate quantity risk, is customer diversity.

There is the unresolved issue of the relationship between customer diversity and retail risk. There are several theories used to understand and manage retail portfolio risks; one such theory is the Modern Portfolio Theory [77]. One of the tenets of the theory emphasises that assets in a portfolio can be diversified to reduce portfolio risk [77]. This theory assumes that assets can be sufficiently distinguished to measure their diversity. From the perspective of the retailer, a household can be considered an asset from which financial risk is experienced.

Socio-demographic can be used to distinguish between household electricity consumption patterns [78, 79]. The use of a metric called "After Diversity Maximum Demand", measured customer diversity and showed that as the number of households served by a retailer increases, the maximum aggregated peak demand from these households decreases [80].

Whilst these studies established a link between the number of customers, maximum aggregated peak demand, and quantity risk, there are three important observations made. Firstly, diversity is a measure of the variety (richness) and relative abundance (evenness) of distinct members in a group [81]. In that sense, the metric "After Diversity Maximum Demand" does not measure richness or evenness between distinct groups of households [82]. The "After Diversity Maximum Demand" metric only measures electricity use within a specific customer class.

Secondly, the "After Diversity Maximum Demand" metric is only designed to measure maximum aggregated peak demand [82]. Whilst peak demand is related to quantity risk, it does not on its own give a complete picture of the variation in electricity use between customers [83].

Thirdly, "After Diversity Maximum Demand" is not a consistent measure of customer diversity because of the metrics dependence on the maximum demand of an electrical system [84]. Since maximum demand changes from day to day and season to season; continuously changing even though the variety (richness) and relative abundance (evenness) of distinct groups of customers do not.

Given the fact that current measures of customer diversity appear to be inadequate, it is reasonable to assume that the influence of socio-demographic diversity on retail portfolio risk remains largely unexplored especially in the context of the large-scale deployment of residential energy management systems. This is an important issue because deploying energy management systems on a large scale assumes that there is full understanding of the factors that influence portfolio outcomes. If there is little evidence to clarify the influence of customer diversity on retail risk, then there would be uncertainty in how energy management systems would influence risk and consequently the cost and benefits to the retailer.

2.3.4 Inability to select appropriate customer demand response baselines

Closely tied to the cost-benefit for customers and retailers is another fundamental issue currently overlooked when modelling these devices; the selection of a baseline load profile. A baseline load profile is an estimate of the amount of electricity that a customer would have used were they not participating in demand response [85]. The amount of energy saved by a residential energy management system is measured as the difference between the load profile produced by the device and a baseline load profile. Based on these electricity savings, economic benefits such as customer bill savings, tax savings and emissions savings are calculated.

Unfortunately, a close inspection of past literature reveals that most studies that model these devices use historical data [86] as the baseline against which to measure the performance of residential energy management systems. There is consensus amongst researchers in the field of demand response measurement and verification that the raw historical data of electricity usage may be insufficient to accurately describe what a customer might do in the future [87]. This is why there has been much research in developing different methods to create more accurate baselines to measure the amount of electricity a customer saved during demand response [87]. Examples of such methods include “Exponential Smoothing” method which weights past observations of electricity use with exponentially decreasing weights to forecast future electricity use [88]; the “High X of Y” method which uses the average of the X highest “daily kWh usage” days from a pool of Y most recent days as the baseline for the hourly electricity use for the current day [88]. Table 2.5 provides a list of commonly used baseline methods [89].

Table 2.5. Nine methods generally used for creating customer baselines

Type of Baseline	Definition
Historical Data	This is raw data collected from the smart meter
Last Y days	Historical smart-meter data is obtained and the average demand use for every hour of the last Y most recent days is used to determine the hourly demand baseline for the current historical day.
Low X of Y days	Historical data is obtained and the average demand use for every hour of X days with the lowest total demand out of the last Y most recent days is used to determine the hourly demand baseline for the current historical day.
Mid X of Y days	Historical data is obtained for the Y most recent days. These days are sorted in order of increasing total daily demand. The average demand use for every hour of the middle X out of the sorted Y most recent days is used to determine the hourly demand baseline for the current historical day.
High X of Y days	Historical data is obtained and the average demand use for every hour of X days with the highest total demand out of the last Y most recent days is used to determine the hourly demand baseline for the current historical day.
Exponential Moving Average	Historical data is obtained and the moving average of the customer's load for every hour is calculated. The baseline for the current historical day is the weighted sum of the moving average and the hourly demand for the current day. The weighting for the moving average is α and the weighting for the current day is $(1-\alpha)$; where α is in the interval $[0,1]$.
Linear Regression	A linear regression equation is constructed from variables that may affect the hourly electricity use of the current historical day. A simple construction would be to construct a linear regression equation using the historical hourly demand of the last Y days to predict the baseline hourly demand of the current day.
Polynomial Interpolation	With this method for every hour historical data of the past recent Y days and the future most recent Y days are used collected and a polynomial (usually of degree 4) is fitted to the data. The polynomial is then used to determine the value of demand for every hour of the current day. This method usually involves 24 polynomials (one for every hour).
Neural Network	A simple feedforward neural network is trained with input being historical data from the collection of variables that may affect the customer demand for the historical current day. In the simplest case historical hourly demand of the first Y days in the data set is used to train the network. The network is then used to predict hourly demand for the next Y historical days.

Baselines created from each method are usually adjusted using a multiplicative adjustment technique [90]. In general, once the reduction in demand is calculated, the estimated baseline is adjusted to consider any special conditions (for example change in weather or unusual demand use) at the time of the demand response period. Nevertheless, because baselines are estimates of the amount of electricity the customer “would have used”, baselines are inherently imperfect [91]; that is, they can never accurately measure what “would have occurred”. Consequently, selecting an optimal baseline method to create a baseline load profile has remained an outstanding issue [91]. This issue is one of the major reasons why there is not a widespread use of demand response technologies such as residential energy management systems in households [92, 93]. Simply put, if an appropriate baseline is not used to measure the demand response of customers then there would be inaccuracies in determining the cost benefit of residential energy management systems. This in turn would affect the retailer’s ability to accomplish tasks such as economic feasibility studies, revenue-risk modelling and justifying compensation to customers for demand response.

2.4 Possible solutions to address challenges

2.4.1 A new modelling approach

The limited amount of appliance data has restricted the number of households that can be examined when looking at the benefit and cost of residential energy management systems to different customers [57, 94]. This by extension has limited the scale and depth of analysis that can be done on the operation of residential energy management systems [59, 60]. Another study highlighted that the purpose of these devices is to modify the load profile of a household [95]. Therefore, the presence of these devices can be modelled directly from the load profile of a household [95]. It is clear that load profiles represent the aggregate of result of electricity consumption and production of the household [96]. With the advent of wide scale use of smart-meters and improvements in load profile modelling, finding large stores of household load profile data is remarkably easy. For example, the creation of a load profile generator capable of load profiles for several thousand households using data from 60 predefined households in

Germany [97]. Other prominent examples of datasets that contain large stores of household energy use data is given in Table 2.6.

Table 2.6. Large sources of household energy consumption data

Dataset	Description
Residential Energy Consumption Survey (RECS) [98]	A 2005 survey that collected data from 4,381 households that were statistically selected to represent the 111.1 million housing units in the U.S.
Smart-Meter Energy Consumption Data in London Households [99]	This dataset contains energy use readings for 5,567 London Households that took part in the "Low Carbon" London project between November 2011 and February 2014.

The autoregressive integrated moving average time series model is suggested as one of the most convenient methods for modelling household electricity consumption [100]. Autoregressive integrated moving average models are considered to provide very accurate forecasting as well as modelling results whilst considering seasonal changes in data [101]. However, using autoregressive integrated moving average models to assess the behaviour of residential energy management systems has received very little attention.

2.4.2 Modifying the load profile of households

Residential energy management systems can reduce electricity use or shift electricity use. If an autoregressive integrated moving average model can be used to model the load profile of a household and residential energy management systems act to modify household load profiles, then it is possible that autoregressive integrated moving average models can be used to model the behaviour of residential energy management systems. However, very little research has been done in this area.

Reducing electricity use in the household often results in a reduction in the load profile of the household [102]. This reduction in load profile means that the average and peak-to-average electricity use of the household is reduced [102]. This has clear benefits for the retailer (reducing the cost of purchasing electricity) and customer (resulting electricity bill savings). Therefore, if an autoregressive integrated moving average model is to be used to model the change in load profile produced by residential energy management systems, this change must be tied to the benefits that the customer and retailer can experience from these systems.

On the other hand, load shifting, and its potential benefits for the customer and retailer is a bit more complex. Demand response that takes the form of load shifting can result in the retailer increasing profit [103]. Load shift involves moving use of an appliance from one period to another. However, it can be extrapolated from [104], that when shifting appliance use, for the customer to reduce their electricity bill and the retailer to make an increase in profit, there are certain price conditions for hourly retail tariff (r_t) and hourly spot price (s_t) that must hold. Table 2.7 shows the conditions that must hold when shifting load from period "a" to period "b" so that both the customer and retailer benefits from demand response.

Table 2.7. Price conditions for retailer and customer benefitting from load shifting

Condition	Explanation
$(s_t)_b < (s_t)_a$	Spot price in period "b" must be less than the spot price in period "a". This means that the cost of providing electricity to the customer is less for the retailer.
$(r_t)_b < (r_t)_a$	Retail tariff in period "b" must be less than the retail tariff in period "a". This means that the cost of electricity for the customer is reduced; that is the customer makes savings in their electricity bill. However, the retailer makes a reduction in revenue as a result.
$(r_t)_b - (s_t)_b > (r_t)_a - (s_t)_a$	The profit per kWh made from period "b" is higher than the profit made per kWh during period "a". This implies that the retailer can make an increase in profit if load is shifted from period "a" to period "b".

If the three conditions listed in Table 2.7 hold then the retailer can make an increase in profit whilst the customer makes savings on their electricity bill. Nevertheless, whilst a benefit sharing approach to evaluate the impact of reflexive demand shifting on retail revenue [104], the authors never fully explored these conditions and explained in detail what this means for demand response devices such as residential energy management systems.

It must be noted that ensuring that these conditions hold so that the customer and retailer are both able to benefit from demand response involves knowing the retailer tariff, spot price and amount for load that can be shifted per customer. It is also clear that if given the option to reduce load (which will result in a loss of profit for the retailer) or to shift load (which may result in an increase in profit whilst helping the customer reduce their electricity bill), then shifting load is preferred.

The retailer obviously cannot achieve that level of monitoring for every customer (particularly if the retailer has hundreds or even thousands of customers). It is also obvious that the customer may not want to, or have the time to, engage in determining which is the best load to shift and at what period. Therefore, having residential energy management systems that can make sure calculations is an asset for the customer and retailer.

Residential energy management systems that can make sure decisions and can even take into account the stochasticity associated with electricity spot price fluctuations has been evaluated [105]. Therefore, if a generalised model for a residential energy management system to be created based on the load profile of a customer, this model must be able to perform load shifting as well as load reduction.

If a generalised model is created without appliance information, then an important issue is being able to justify the load shifting; that is, how does one ensure that any shifts that the generalised model would make to a load profile for a customer can actually be performed by the customer?

This question is answered by presenting models that can be used to predict demand response shifting behaviour of a customer [106]. The models are based on price elasticity of demand and three different types of load (single period, multi-period and composite loads) and are shown in Table 2.8.

Table 2.8. Demand response models for different types of loads in a household

Load types	Definitions	Equations representing load types
Single period elastic load	These are loads $d_S(i)$ whose power consumption at certain period is only influenced by the electricity price within that period. The user decided which loads fall under this category but generally loads such as household lights usually fall under this category. These loads are modelled using self-elasticity $E(i,i)$.	$d_S(i) = d_0(i).\left(\frac{\rho(i)+A(i)+pen(i)}{\rho_0(i)}\right)^{E(i,i)}$
Multiple period elastic Load	These are loads $d_M(i)$ whose power consumption at certain period is influenced only by the electricity price within other periods. The user decided which loads fall under this category but generally loads such as rechargeable batteries usually fall under this category. These loads are modelled using cross-elasticity $E(i,j)$.	$d_M(i) = d_0(i).EXP\left\{\sum_{\substack{j=1\\ j\neq i}}^{T} E(i,j)ln\left(\frac{\rho(j)+A(j)+pen(j)}{\rho_0(j)}\right)\right\}$
Composite elastic load	These are loads $d_C(i)$ whose power consumption at certain period is influenced by the electricity price within the current time period and other periods. The user decided which loads fall under this category but generally loads such as electric vehicles usually fall under this category. These loads are modelled using cross-elasticity $E(i,j)$.	$d_C(i) = d_0(i).EXP\left\{\sum_{j=1}^{T} E(i,j)ln\left(\frac{\rho(j)+A(j)+pen(j)}{\rho_0(j)}\right)\right\}$

For this research $A(j) = 0$ and $pen(j) = 0$ for all $A(j)$ and $pen(j)$

where	
ρ_0	Initial price within a certain period
d_0	Initial demand within a certain period
∂d	Difference in demand between two periods
$\partial \rho$	Difference in price between two periods
$E(i,i)$	Self-elasticity within period *i*
$E(i,j)$	Cross elasticity between period *i* and *j*
$A(j)$	Incentive received by customer for reducing demand during period *j*
$pen(j)$	Penalty for not reducing demand during period *j*

Price elasticity of demand, shown in Table 2.9, is an economic measure that indicates by how much a customer is willing to change demand if price changes.

Table 2.9. Price elasticity of demand

	Definitions	Equation representing elasticity
Price elasticity of demand	The degree to which the effective demand changes as its price changes	$E = \frac{\rho_0}{d_0} . \frac{\partial d}{\partial \rho}$

When the retail price is low for a given period, customers generally will use more electricity during that period and when the retail price is high then the customers are willing to reduce or shift load to reduce demand [107]. The study also supports the use of price elasticity of demand models to represent customer behaviour and analyse situations to determine situations where the benefits of the retailers' demand response can be maximised. Therefore, these elasticity models can be used to validate any shifts (or reductions) in demand that a generalised model of residential energy management system makes.

If an autoregressive integrated moving average model is to be used to represent load shifting, then the model must take the conditions listed in Table 2.7 into account. This would simply be a matter of shifting load and after shifting representing the resulting profile into an autoregressive integrated moving average model.

2.4.3 A new approach to selecting a baseline

Selecting a baseline necessarily involves examining the baseline's accuracy and bias [24]. An "Overall Performance Index" was developed to measure the performance of a given residential customer baseline. This index is given in Equation (2.1).

$$\lambda|\alpha| + (1 - \lambda)|\beta| \tag{2.1}$$

where

λ	Weight indicating relative importance of baseline
α	Baseline accuracy
β	Baseline bias

The strength of the research is that, in the process of creating the "Overall Performance

Index", the importance of finding an optimal balance between accuracy and bias of a baseline was considered. Nevertheless, the impact that using a homogenous baseline may have on the benefits that different customers may receive from a demand response program was not considered.

To address this issue, studies such as [108] went one step further and examined the merits of using different self-reported baselines to measure the performance of a demand response program. According to the research, the system operator recruits consumers for a demand response program. The recruited customers report their own baselines to the operator. The selected customers reduce their load during a demand response event and are rewarded for their services (or are penalised for deviating from their expected load reduction), based on the reported baselines. The weakness of this research is that self-reported baselines only considered the economic benefits of the customer and did not consider the direct and indirect ramifications of demand response for the retail portfolio of the electricity provider. Therefore, these baselines do not fully represent the benefits of all stakeholders involved in demand response programs.

Other studies such as [109] did extensive analyses to show that the selection of a baseline can and does affect the benefits that the retailer receives from a demand response program. Furthermore, demand response programs must be designed to maximise the social and economic welfare of all stakeholders [110]. These general observations point to the fact that a basic economic model can be created to help select an appropriate baseline to measure the performance of residential energy management systems.

However, model complexity and model fit must be examined; model complexity measures the number of parameters needed by the model to accurately capture patterns processes and relationships between variables in the data [111]. Model fit measured how well the model generalises to other similar data [111]. Increasing model complexity decreases model fit and vice versa. It is for this reason that it is advisable to use metrics such as Bayes Information

Criterion to measure model fit and complexity. The smaller the Bayes Information Criterion values the better the balance between model complexity and fit [112]. Therefore, in creating an economic model to select an optimal baseline to measure demand response, the complexity and fit of the model needs to be addressed.

Developing a robust well-balanced model for selecting a baseline method and justifying this selection based on the economic advantage this baseline would provide to the customer and retailer a major contribution to the current state-of-the-art. Moreover, developing a model for residential energy management systems that consider the baseline used to measure its performance would add value to existing literature.

2.5 Concluding remarks

Several issues have been examined with regards to the weaknesses associated with the large-scale modelling of residential energy management systems. Possible solutions to these issues have been outlined. In light of the literature review, strategies for dealing with each of these issues can now be developed.

Chapter 3

Developing a generalised model for residential energy management systems

3.1 Introduction

From studying the literature, it is apparent that a new modelling approach needs to be developed for residential energy management systems. It was established that using disaggregated appliance data limits the depth and scope of analysis that can be done with these devices. Therefore, any improvements in the modelling approach of residential energy management systems necessarily involves finding a different method to model the operation of these devices. Furthermore, it was suggested that the load profile, which represents the sum of all the energy activities (production and consumption) of the household, can be used to directly model the operation of residential energy management systems.

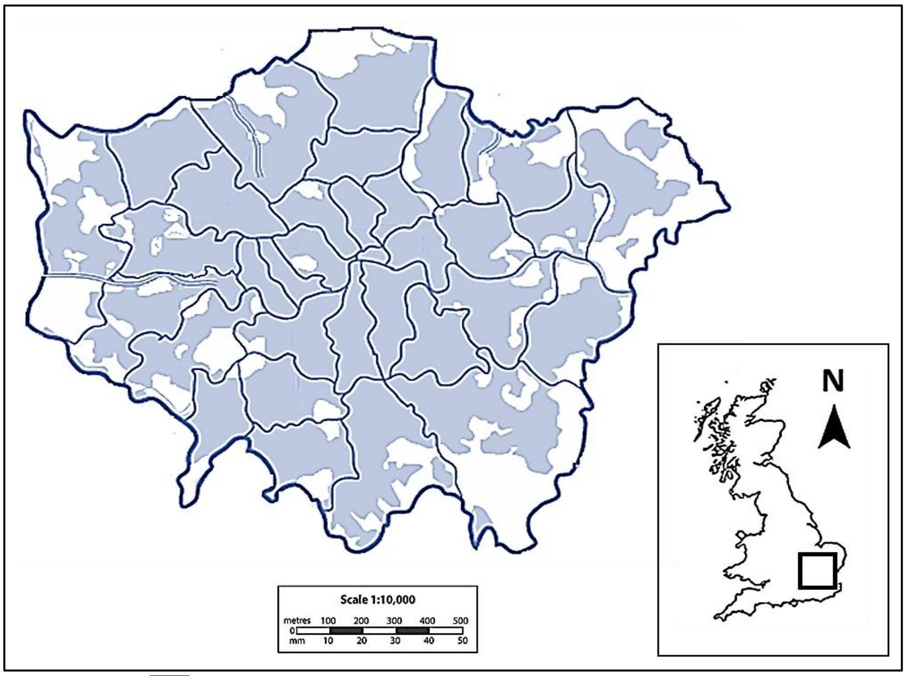
To address the first objective of this research it was apparent that a generalised model of a residential energy management system that relies on load profile data to model the demand response operations of the device needed to be developed.

3.2 Procuring research data

From the literature, several databases with large stores of household electricity use data were identified as having potential to inform this work. To provide context for this research, households that participated in “Low Carbon London” project in the UK were chosen as the data source for analysis. That project began April 2010 and was initiated in response to the commitment by the UK to reduce greenhouse gas emissions by 80% by 2050 [113].

One of the outcomes of the project was the classification of the 5,567 households participating in the project into eighteen socio-demographic groups [114] and two tariff types (Flat-rate and Time-Of-Use tariff) [114]. These households were considered a representative sample of all residents in London [115]. The categorisation given to the households was created by an American multinational professional services and information technology company headquartered in Arlington, Virginia. The classification originally called “A Classification of Residential Neighborhoods” (ACORN), is based on an optimisation segmentation tool which uses several socio-demographic and economic factors including household income, mean age of household occupants, household tenure, number of children in household and social media usage [116].

Consequently, the project provided a large source of validated household energy use data categorised by the socio-demographic of customers and the tariff structure. A complete description of the characteristics of each group is given in Table of Appendix A. The location of these households is shown in Figure 3.1.



General location for households used in this research [115]

Figure 3.1. Location of households in the “Low Carbon” London Project, UK

Moreover, close-out reports on the project confirmed that the socio-demographic profile of customers, and the tariff customers pay, influenced both peak and average electricity use [115]. This made participating households an excellent testbed for determining how the performance of residential energy management systems is jointly influenced by the socio-demographic and tariff rate when assessed on a large scale.

Upon selecting the "Low Carbon London" project, of the 5,567 households, data for a sample of 5,379 households was available from [117]. Of the 5,379 households, 4,286 households paid a Flat-rate tariff of 0.14228 £/kWh [118]; the other 1,093 households paid a Time-Of-Use tariff. The Time-Of-Use tariff price signals were "High" (0.6720 £/kWh), "Normal" (0.1176 £/kWh) and "Low" (0.0399 £/kWh). The tariff prices were given a day ahead through the smart meters installed at the customers' premises. The time the price signal was issued was included in the dataset.

The 5,379 households selected were divided into 36 subgroups based on the 18 socio-demographic types and 2 tariff structures identified in the "Low Carbon" London project. The half-hourly electricity use data for 5,379 households needed to be converted into a manageable form to reduce both the complexity and time taken to perform any sort of analysis on this data. Therefore, the average monthly load profile for a typical customer in each of the 36 customer groups from April 1st, 2010 to December 31st, 2012 was determined. The result was 36 average monthly load profiles that represented the electricity use of households in the different subgroups. Appendix B provides the average monthly load profile for a typical customer for each of the 36 groups examined.

After dividing the customers into 36 subgroups and finding the average monthly load profile for each group, it was assumed that all households had a residential energy management system installed. This was to evaluate how these devices operated for different socio-demographic groups and tariff types. Since the households were scattered over a small single geographic region, as highlighted in Figure 3.1, it was not necessary to consider the spatial distribution of the households and its effects on energy demand when modelling the operation of the residential energy management systems. Consequently, this simplified the level of analysis and the number of assumptions that had to be made in simulating the presence of these devices amongst households.

The second set of data selected was spot price data from the N2EX Great Britain power market. N2EX is a joint venture between “Nord Pool Spot” and “Nasdaq OMX Commodities AS” providing market clearing services and a physical power exchange for the electronic trading of power contracts [119] for over 60 energy suppliers in the UK [119, 120]. The N2EX market is Europe’s third largest power market by volume, trading 49% of Great Britain’s energy consumption [121]. It provides reliable historical reference spot prices so that retailers can forecast future spot prices [122]. Upon selecting the N2EX market, hourly electricity spot price data from April 1st, 2010 to December 31st, 2012 was obtained and used to characterise the spot price that a typical retailer in London would face. The spot data were used alongside the retail tariff data of the “Low Carbon” London Project to provide information necessary to assess the large-scale effects of residential energy management systems.

3.3 A generalised model for residential energy management systems

3.3.1 Conceptual Model

Owing to the limitations of using appliance data as discussed in Chapter 2 (Literature Review), this research adopted a novel approach that used load profile data to model the operation of residential energy management systems. This conceptual approach is shown in Figure 3.2.

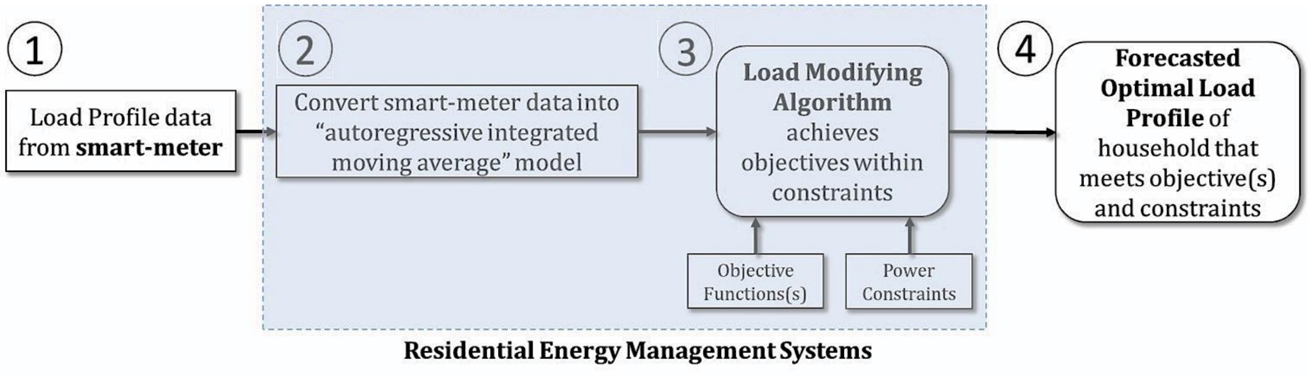


Figure 3.2. Model characterising a residential energy management system

Load profile data from smart meters installed at homes formed the input to the residential energy management system. The load data were converted to an autoregressive integrated moving average model (as indicated in step 2 of Figure 3.2). An autoregressive integrated moving average model is simply a regression equation that is based on the idea that information from recorded past electricity use of the household can be used to forecast future electricity use [123]. An autoregressive integrated moving average model was chosen because it has been used frequently, and with a high degree of success, as a benchmark model [123] for time series analysis and forecasting of residential electricity use. The autoregressive integrated moving average model, more formally, $\mathrm{ARIMA}(\mathrm{p}, \mathrm{d}, \mathrm{q})$, is shown in Equation (3.1).

$$d_t = \sum_{n=1}^{p} \varphi_n . d_{t-n} + \sum_{m=1}^{q} \theta_m . e_{t-m} \tag{3.1}$$

From Equation (3.1), the dependent variable (d_t) is the electricity use value to be forecasted and the independent variables "d_{t-n}" and "e_{t-m}" are past hourly electricity use, and past hourly forecasted errors respectively. The variable "t" represents the time horizon under consideration, "p" represents the number of past electricity use values needed to forecast "d_t" and "q" the number of past forecasted error values needed to forecast "d_t". It is important to note that past electricity use values "d_{t-n}" can be calculated as follows:

When

$n = 0$: $d_t = d_t$

$n = 1$: $d_{t-1} = d_t - d_{t-1}$

$n = 2$: $d_{t-2} = (d_t - d_{t-1}) - (d_{t-1} - d_{t-2})$

$n = 3$: $d_{t-3} = (d_t - d_{t-1}) - (d_{t-1} - d_{t-2}) - (d_{t-2} - d_{t-3})$

$\vdots$

Expressions for past forecast errors (e_{t-m}) are similar. The key to representing load profile data as an autoregressive integrated moving average model is to find the regression coefficients of "φ_n" and "θ_m" that accurately represent the electricity use profile under consideration. A statistical software package in MATLAB was used to accomplish this. MATLAB has two functions "*estimate*" and "*arima*" [124] that can be used to determine the autoregressive integrated moving average representation of a given time series. An example of how this is done can be found in [124].

Equation (3.1) was modified to express the average and peak-to-average features of the electricity use profiles. The independent variable (d_{t-n}) (past electricity use values) was expressed as a linear combination of past average electricity use values (A_{t-n}) and past average-to-peak electricity use values (Q_{t-n}) as shown in Equation (3.2):

$$d_t = \sum_{n=1}^{p} \varphi_n [A_{t-n} + Q_{t-n}] + \sum_{m=1}^{q} \theta_m . e_{t-m} \tag{3.2}$$

Since residential energy management systems are often required to produce a percentage reduction (k_1) in average electricity use [125] during a demand response event, the overall effect is a reduction in the forecasted value (d_t) as expressed in Equation (3.3).

$$d_t^{**} = k_1 . \sum_{n=1}^{p} \alpha_n . A_{t-n} \; + k_1 \sum_{n=1}^{p} \beta_n . Q_{t-n} + k_1 . \sum_{m=1}^{q} \theta_m . e_{t-m} \tag{3.3}$$

Similarly, these devices can also be required to make a percentage reduction (k_2) in hourly peak-to-average electricity use [10]. This was represented as a further reduction (${d_t}^*$) as expressed in Equation (3.4).

$$ {d_t}^* = k_1 . \sum_{n=1}^{p} \alpha_n . A_{t-n} + k_1 . k_2 \sum_{n=1}^{p} \beta_n . Q_{t-n} + k_1 . \sum_{m=1}^{q} \theta_m . e_{t-m} \tag{3.4} $$

As such, Equation (3.4) was used to characterise the forecasted effect that residential energy management systems have on the hourly electricity consumption (d_t) of a typical household. Equation (3.4) also formed the model used to represent the operation of these devices. Hence, the total reduction in electricity consumed (D^*) is given by Equation (3.5).

$$ D^* = \sum_{t=1}^{T} {d_t}^* \tag{3.5} $$

3.3.2 Objective function for the device

The residential energy management system model also required its objectives and constraints to be specified. The objectives for the load profile indicate why the load profile is being reduced and what the benefits and costs (for the customer and retailer) are for that reduction. It can therefore be used to find the optimal total reduction in electricity consumed (D^*) that would maximise the benefits and minimise the cost associated with these devices. The constraints, on the other hand, set limits on the amount of load that can be reduced.

The objectives chosen for this research, although not exhaustive, covered a range of possible functions, as has been outlined in previous review articles [66, 126]. These functions can be divided into two groups: objectives associated with maximising the benefits to the customer [126], and objectives associated with minimising the cost of having these systems [126]. The objective functions associated with maximising the benefits are as follows:

(i) *Maximise electricity bill savings.* Electricity bills savings are the money the customer saves as a result of the energy management device reducing electricity demand. This is simply the difference between the electricity bill of the customer before and after installing the device [18].

(ii) *Maximise emissions savings.* Emissions are the amount of greenhouse gasses (primarily carbon dioxide) released into the atmosphere for every kilowatt-hour of electricity provided to the customer. Emissions savings arise when customers reduce the number of kilowatt-hours of electricity that they consume. This results in lower cost for the customer as well as less emissions into the environment [127]. The monetary value of the emissions savings is given as the product of the reduction in electricity (kilowatt-hours) used by the household (as a result of the operation of the residential energy management system), the amount of CO_2 (in kilograms per kilowatt hour) not released into the atmosphere and the social cost per kilogram of CO_2 [127].

(iii) *Maximise tax savings.* Every electricity bill has a tax component included in the bill. The authors of [68] introduced the concept of a *tax ad valorem,* which is simply the reduction in taxes charged to the customer's electricity bill calculated as a proportion of their electricity use after demand response. As indicated by [68], given the original tax (τ) reduced tax ($\tilde{\tau}$), this can be found using Equation (3.6). (D* was previously defined in Equation (3.5)).

$$\tilde{\tau} = \frac{\tau}{D^*} \tag{3.6}$$

The reduction in tax results in a reduction in the electricity bill. This reduction is called the tax savings from the bill.

(iv) *Maximise retail profit.* The electricity retailer buys electricity from the wholesale market at a given cost and generates revenue by selling it to the residential customer (as well as to other customers). The revenue obtained by the retailer is reflected in the electricity bill of the customer. It is suggested that demand-side management technology can be used to reduce the electricity bill of the customer and in the process increase the profit associated with the retail portfolio of the retailer [69]. It has already been indicated in Chapter 2 that maximising retail profit involves load shifting and this load shifting must satisfy the three conditions given in Table 2.7. However, very little has been done in past literature to develop a load shifting algorithm based on these price conditions. Therefore, part of making use of this objective function would involve creating a load shifting algorithm to ensure the function is maximised.

The objective functions associated with minimising the cost of these devices to the customer is given as follows:

(i) *Minimising customer discomfort.* Customer discomfort is considered one of the primary costs of installing these devices. It is measured using numerous indices [86]; one of the most common being the Taguchi loss function [128]. This function gives a relationship between the reduction in consumption of a good (in this case electricity) and the loss of satisfaction the consumer experiences [128].

(ii) *Minimising simple payback period.* Another consideration is the initial purchase cost and the consequent simple payback period of the device [129]. Simple payback period is the amount of time taken to recover the cost of the device. Thus, an expensive device leads to a longer payback period and more discomfort for the customer [27]. The payback period "n" (given in months) is simply given as the cost of the device divided by the savings per month produced by the energy management device.

A summary of the parameters and formulas used to quantify each objective as well as the references supporting each formula is given in Table 3.1.

Table 3.1. List of objectives used in this research and references for their formulas

Objective Functions	Formulas	Parameters	Reference
Maximise electricity bill savings (J_1)	$J_1 = \sum_{t=1}^{T}[(d_t - d_t{}^*) \times r_t]$		[18]
Maximise the emissions savings (J_2)	$J_2 = \sum_{t=1}^{T}[(d_t - d_t{}^*) \times c \times c_r]$	$c = 70$ £ $c_r = 0.003\ kg/kWh$	[127]
Maximise tax savings (J_3)	$J_3 = \sum_{t=1}^{T}(\tau . d_t - \tilde{\tau} . d_t{}^*)$	$\tau = 0.05$	[68]
Maximise retail profit (J_4)	$J_4 = \sum_{t=1}^{T}[(d_t - d_t{}^*) \times (r_t - s_t)]$		[69, 130]
Minimising customer discomfort (J_5)	$J_5 = \frac{X}{Z} \times Y$		[86, 131]
Minimising payback period (J_6)	$J_6 = \delta\left(p_p . J_1 - C_p\right)^2$	$C_p = 273.13$ £ $\delta = 1£^{-1}$	[27, 129]

where

$$X = \sum_{t=1}^{T}[d_t \times r_t]$$

$$Y = \sigma^2{}_t{}^* + \sum_{t=1}^{T}[(d_t{}^*)^2]$$

$$Z = \sigma^2{}_t + \sum_{t=1}^{T}[d_t{}^2]$$

The benefit and cost objectives functions shown in Table 3.1 were combined into a single benefit-cost objective function given by Equation (3.7). This objective function, when maximised, leads to the optimal load profile of the household.

$$Maximise\ b_c = \frac{w_1.J_1 + w_2.J_2 + w_3.J_3 + w_4.J_4}{w_5.J_5 + w_6.J_6} \tag{3.7}$$

where

b_c	Optimal benefit-cost ratio for customer
$J_1, J_2, J_3, J_4, J_5, J_6$	Objective function of energy savings (J_1), emissions savings (J_2), tax savings (J_3), retail portfolio savings (J_4), customer discomfort (J_5) and payback period (J_6).
$w_1, w_2, w_3, w_4, w_5, w_6$	Weights that take a discrete value (either 0 or 1).

In formulating this, the weights associated with the objective functions indicate a binary choice (i.e. 0 or 1). If an objective is being considered when maximising b_c (Expression (3.7)) then its weight is given a value of 1, if it is neglected the weight is 0. Invariably, when the device is installed in a home, the customer will experience discomfort and will have to spend money over time to pay for the installation. Therefore, throughout this research, the weights w_5 and w_6 were set at a constant value of 1. This means that the cost to each household (even though it may vary from household to household) is a constant consideration.

It was important to prove that the objective function shown in Expression (3.7) can be maximised; that is, it has a global maximum. If Expression (3.7) does not have a global maximum, then it cannot be used to find an optimal load profile (D^*) and consequently the proposed approach to modelling residential energy management systems on a large scale would not be a sensible one. Therefore, proving that the function has a global maximum is a necessary step in the model's development. A necessary condition for the model to have a global maximum is given in Expression (3.8).

$$b_c > 0 \tag{3.8}$$

Expression (3.8) was derived from two properties of functions with global maximum. The first order derivative of Expression (3.7) must be zero (indicating that the function has a saddle point; a point of maximum or minimum) and the second order derivative of the function must be greater than zero (indicating that the saddle point is a global maximum). A full derivation of Expression (3.8) using these two properties is given in Appendix C.

Expression (3.8) is not a constraint on Expression (3.7) but rather simply a property of the function that ensures that it has a global maximum.

3.3.3 Model Constraints

In the process of fulfilling its objectives, there are limits that the device must adhere to.

One of these limits is the reduction in electricity use that the system can produce for the household before it reaches its base load. Hourly base load (B_t) is the ongoing basic amount of electricity required to run the house when household occupants are not actively using any appliances. This base load includes electricity use from devices such as fridges, appliances on standby, wi-fi routers and chargers. In reducing household electricity consumption, the model must ensure that base load is still serviced. This constraint can be given by Expression (3.9).

$$B_t \leq {d_t}^* \leq d_t \tag{3.9}$$

3.3.4 Load profile modifying algorithm

Once the objectives and constraints were outlined, a load profile modifying algorithm was constructed. This algorithm specifies how the device modifies the load profile of the household (represented by the autoregressive integrated moving average model) to fulfil the objectives given while operating within constraints.

According to the references given in Table 3.1, to maximise the functions J_1, J_2, J_3, J_5 and J_6 load reduction has to be used, however, to maximise function J_4 (retail profit), load shifting has to be used. Therefore, the load modifying algorithm was constructed to perform both load shifting and load reduction in order to modify the customer's load profile. The final output of the model consisted of the optimal reduced monthly load profile of the household, the values of the percentage reduction (k_1) in average electricity use, the percentage reduction (k_2) in hourly peak-to-average electricity use and the final benefit-cost ratio b_c gained from the device. A flow chart of the algorithm is given in Figure 3.3.

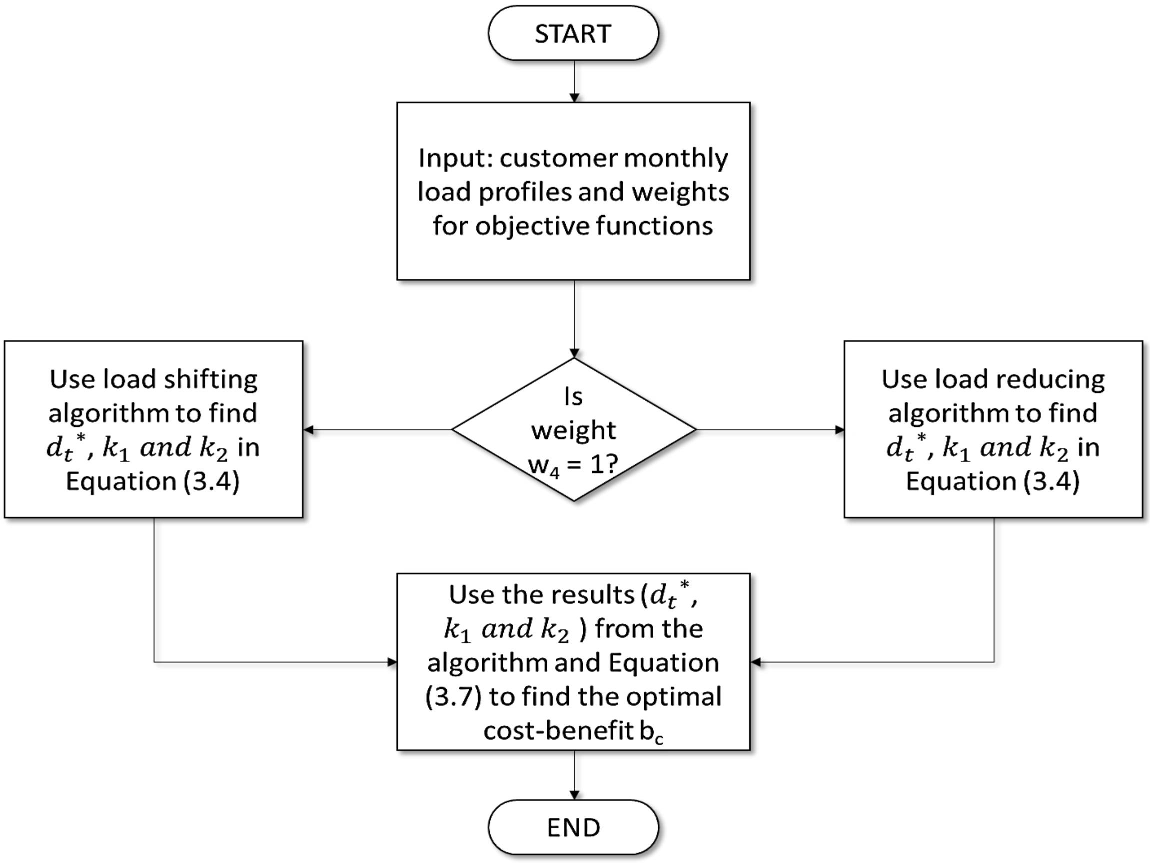


Figure 3.3. Flow chart of load modifying algorithm

According to the flow chart in Figure 3.3, the inputs to the load modifying algorithm are the original load profile of the customer and the weights for the objectives of the residential energy management system. The algorithm then checks whether the retail profit is one of the objectives to be considered (that is, if the weight $w_4 = 1$) when determining the optimal forecast demand response produced by the device. If increasing retail profit is to be considered, then the load shifting component of the algorithm is used to modify the load profile. The load shifting algorithm is given in Table 3.2.

Table 3.2. Load shifting algorithm to modify load profile

Algorithm Input: *load profile of household D, retail tariff* r_t *and spot price* s_t	
1	Get the customer forecasted load profile.
2	Let “a” and “b” be two hours in the forecasted load profile. Initially “a” and “b” are set to the first hour in the forecasted load profile.
3	If the electricity consumed during hour “a” is greater than the electricity use during hour “b” for the forecasted load profile and the amount of profit per kilowatt hour during hour “b” is greater than the profit per kilowatt hour during hour “a” execute line 4 and line 5.
4	New demand for hour “a” = average electricity consumption for hour “a” and hour “b”.
5	New demand for hour “b” = average electricity consumption for hour “a” and hour “b”.
6	If the conditions in line 3 are not true execute line 7 and line 8.
7	New demand for hour “a” = original electricity consumption for hour “a”.
8	New demand for hour “b” = original electricity consumption for hour “b”.
9	Repeat line 2 to 8 for every hour “b” in the forecasted load profile.
10	Repeat line 2 to 9 for every hour “a” in the forecasted load profile.
11	Calculate and store the resulting $k_1$for the new load profile, where $k_1 =$ the average of the new forecasted demand profile divided by the average of the original forecasted demand profile.
12	Calculate and store the resulting k_2 for the new load profile, where $k_2 =$ the standard deviation of the new forecasted demand profile divided by the standard deviation of the original forecasted demand profile.
Algorithm output: *optimal values for* k_1, k_2	

According to Table 3.2, every hour in the load profile is compared to every other hour. If two periods are found such that the conditions given in line 5 of Table 3.2 are true, then the average of the demand is found for the two periods. Finding this average is equivalent to shifting demand from one period to the next so that both periods have the same demand. Although simple, this algorithm does produce an optimal load profile with a reduced peak-to-average demand. Thus, the customer reduces their electricity bill whilst the retailer increases its profit.

One the other hand, if the retail profit is not one of the objectives to be considered (that is, if the weight $w_4 = 0$) then, according to the flow chart given in Figure 3.3, a load reducing component of the algorithm is used. The load reducing component is based on particle swarm optimisation (PSO) procedure and is shown in Table 3.3.

Table 3.3. Load modifying algorithm based on particle swarm optimization

Algorithm Input: *Average Load profile of household*	
1	Initialise number of iterations (number of attempts to get a solution) to 150
2	Initialise number of particles (number of possible solutions to consider in each attempt) to 50
3	For each particle the position (possible solution to $k_1$and k_2) and velocity (rate at which the solution will change) is randomly initialised
4	Measure the fitness (b_c) for each particle. The fitness function simply calculates the value of (b_c) based on inputs: demand profile of household, $k_1$and k_2.
5	Store each particle best fitness (b_c) in "pbest" and store the particle with the overall best fitness in "gbest"
6	For each particle update the position and velocity vectors according the update equation found at [52]
7	Repeat steps 3 to 6 until maximum number of iterations is reached.
Algorithm output: *optimal reduced load profile of household, optimal values for k_1, k_2 and b_c.*	

The algorithm uses a fitness function that calculates b_c using Equation (3.7). The fitness function is shown in Table 3.4. Particle swarm optimisation was chosen as the basis for the algorithm because it is excellent at avoiding suboptimal solutions, is simple to implement, does not add to the complexity of the problem being solved and is efficient in finding optimal (or near optimal) solutions [52].

Table 3.4. Fitness function for the particle swarm algorithm shown in Table 3.3

Algorithm Input: *scenario number, w_1, w_2, w_3 and w_4, load profile data for household and k_1, k_2*	
1	Use the load profile data to create an autoregressive integrated moving average model using Equation (3.2)
2	Use the model to forecast 720 hours (1 month) of future electricity use.
3	Use the load profile data and k_1, k_2 values to create an autoregressive integrated moving average model using Equation (3.4)
4	Use the new model to forecast 720 hours (1 month) of future electricity use.
5	Use the result from line 4 and 5, Equation (3.7) and w_1, w_2, w_3 *and* w_4 to calculate the b_c value for the customer
Algorithm Output: customer cost-benefit ratio b_c	

The final output of the model consisted of the optimal forecasted reduced monthly load profile of the household, the values of the forecasted percentage reduction (k_1) in average electricity use, the forecasted percentage reduction in hourly peak-to-average electricity use (k_2) and the forecasted cost-benefit ratio (b_c) gained from these devices.

3.4 Assumptions made in developing the model

To simplify the complexity of the model, and focus on the key issues of the thesis, several assumptions were made in the initial design of the residential energy management system generalised model.

It was assumed that the customer strictly adheres to optimal demand profile produced by the model. That is, if the residential energy management system made changes to the scheduling and use of appliances within the household, the customer followed the schedule made by the device without deviation. Whilst this assumption may not consistently hold, it is assumed that since the households are from a sample of customers participating in a demand response program (Low Carbon Project) these customers would have made every effort to reduce their electricity use. As such, that assumption made about customer behaviour was kept throughout this research. The customer household was considered a “black box” with only the load profile representing the collective activity within the home including battery storage, energy production from solar PV and electricity vehicle charging.

It was assumed that once the residential energy management system is installed it begins to work immediately and continuously to reduce household electricity demand. Generally it is important to make distinctions between single period, multiperiod and continuous demand response events as the techniques used to model these events are different [106]. Continuous demand response events are easiest to model because there is no need to consider the latency period between communicating the need for demand response (by the retailer) and executing demand response within the household. Such latency periods would need extra modelling considerations that are beyond the scope of this thesis.

Additionally, for simplicity, costs such as installation cost, maintenance cost and consultation fees were not considered when examining device cost. Calculating these costs generally depends on specific retail and market conditions and, as such, was not included in the model. This ensured that the model was as general as possible.

Since residential energy management systems can offer two-way communication [42], it was assumed that the retailer is aware of this and can communicate with the device.

Finally, it was assumed that the electricity retailer is also the aggregator responsible for aggregating the demand response of all households with the residential energy management systems. Compensation (and penalties) paid by the aggregator for customers providing (or not providing) demand response was not considered in this research. This greatly simplified the research process and kept the scope of the thesis manageable.

3.5 Full factorial simulation of the model

Having developed the generalised model of a residential energy management system, in keeping with the objective of this chapter, it was necessary to determine how socio-demographic factors, tariff structure and the choice of operational objectives used by the device interact to influence the reductions in average and peak-to-average electricity use produced by these devices when installed on a large scale.

The 36 average load profiles representing each socio-demographic group were converted into autoregressive integrated moving average models. The best autoregressive integrated moving average model to represent each load profile was determined using a measure called mean absolute percentage error (MAPE) [132]. The mean absolute percentage error is one of the standard metrics used for measuring autoregressive integrated moving average model accuracy [132]. It is calculated as the average absolute percent error for each time period minus actual values divided by actual values [132]. Values of mean absolute percentage error less than 10% indicate that the autoregressive integrated moving average model is very accurate in representing the load profile [132]. This was done to determine whether autoregressive integrated moving average modelling was appropriate for the load profiles used in this research.

The algorithm used is given in Table 3.5.

Table 3.5. Find the autoregressive integrated moving average model for each load profile

Algorithm Input: *36 average load profiles representing each customer group*	
1	For the first customer group set the mean absolute percentage error to 1000000.
2	Set p = 1
3	Set q = 1
4	Set d = 1
5	Create and autoregressive integrated moving average model using the MATLAB function "arima(p,q,d)"
6	Get the new mean absolute percentage error from the model using the MATLAB function "estimate (load profile, arima(p,q,d))"
7	If the new mean absolute percentage error is the lowest error so far for the customer group store the values of p, q and d
8	Repeat line 4 to 7 each time increasing the value of d by 1 until "d" reaches 4.
9	Repeat line 3 to 8 each time increasing the value of d by 1 until "q" reaches 4.
10	Repeat line 2 to 9 each time increasing the value of d by 1 until "p" reaches 4.
11	Repeat line 1 to 10 until all 36 average load profiles belonging to the customer groups are done.
Algorithm Output: *p, q, d, and mean absolute percentage error values for all 36 average load profiles*	

Once the autoregressive integrated moving average model representing each of the 36 load profiles was found and it was determined that the 36 load profiles can be accurately represented by these models, they were then paired with the residential energy system model and subjected to a full-factorial analysis of variations from its objective function. The weights w_1 to w_4 given in Equation (3.7) were set to "1" or "0" to produce the combinations given in Table 3.6.

Table 3.6. Scenarios outlining possible combination of objectives for device

Scenario Number	w_1	w_2	w_3	w_4	w_5	w_6
1	0	0	0	0	1	1
2	1	0	0	0	1	1
3	0	1	0	0	1	1
4	1	1	0	0	1	1
5	0	0	1	0	1	1
6	1	0	1	0	1	1
7	0	1	1	0	1	1
8	1	1	1	0	1	1
9	0	0	0	1	1	1
10	1	0	0	1	1	1
11	0	1	0	1	1	1
12	1	1	0	1	1	1
13	0	0	1	1	1	1
14	1	0	1	1	1	1
15	0	1	1	1	1	1
16	1	1	1	1	1	1

From Table 3.6 there are 16 possible combinations (or scenarios) of objectives that the generalised model characterised in this research can have. For example, in "case 14" the device is operating to achieve electricity bill savings, tax savings for the customer and retail profit for the electricity provider (whilst considering the discomfort and cost of the device). The fact that weights w_5 and w_6 are kept constant means that the effects of cost were always considered throughout the research.

Each scenario was examined for each of the 36 subgroups created, to understand how the reductions in average and peak-to-average electricity use from these devices vary with socio-demographic, tariff structure and combination of objective functions. The algorithm used to do this is given in Table 3.7.

Table 3.7. Algorithm for generating optimal benefit cost for each customer group under each tariff type

Algorithm Input:	*Load profile data for all households*
1	Find the representative average monthly load profile for the first household subgroup.
2	Use the Monte Carlo generator (shown in Equation (3.10)) to generate 10000 load profiles from the representative average monthly load profile.
3	Use the algorithm given in Figure 3.3 to find the optimal reduced load profile of household, optimal values for k_1, k_2 and b_c for each of the 10 000 load profiles.
4	Find the average k_1, k_2 and b_c values from the 10 000 results and store the final averages.
5	Repeat steps 1 to 4 for the other 15 scenarios presented in Table 3.6.
6	Repeat steps 1 to 5 for the other 35 customer groups.
Algorithm Output:	*576 average values of k_1, k_2 and b_c (one for each scenario and customer group combination)*

In accordance with the algorithm, the average monthly load profile created for each of the 36 customer groups was used in a Monte Carlo simulation. For the first customer group (i.e., "Lavish Lifestyles" customers under a flat-rate tariff), 10,000 monthly electricity use profiles were generated using a Monte Carlo generator shown in Equation (3.10).

$$[d_t]_m + (-1)^{round(rand)} \times [\sigma_t]_m \times rand = [d_t]_m + N_m \tag{3.10}$$

where

$[d_t]_m$	vector containing hourly energy consumption data for the average monthly load profile under examination
$[\sigma_t]_m$	vector containing hourly standard deviation of energy consumption data for the average monthly load profile under examination
$rand$	random number generator that generates numbers in the interval [0,1]
N_m	represented the noise associated with human activity within the home

Following from research done by authors of [1], it was assumed that the load profile of households was normally distributed. This normal distribution property of the data holds for the households participating in the "Low Carbon" London project [1]. This lends support to the use of the Monte Carlo generator shown in Equation (3.10) which is based on generating random values from a normal distribution.

For each enumerated set of objective functions, or "scenarios", (as shown in Table 3.6), the 10,000 load profiles generated were fed into the residential energy management system model to find 10,000 values for the reductions in average and peak-to-average electricity use produced by these devices for the customer group. Using the 10,000 results, the average reductions in average and peak-to-average electricity use for each subgroup was found. The optimal cost-benefit ratios were also found and stored.

3.6 Validating the model's results

Initially, to determine the accuracy of the results obtained from the model, the range of values for the reduction in average demand and peak-to-average demand found for all customer groups paying a Flat-rate and Time-Of-Use tariff were first compared to those recorded in past literature.

Subsequently, using a more rigorous method of model validation, the results of the model were compared to demand response models created by [133]. A general method that uses elasticity of demand to determine the likely reduction in electricity use that customers in demand response programs would produce if given electricity price signals [133]. In their research the authors proposed that there are three types of load that should exist in order for customers to be able to participate in demand response through price signals. These loads as well as the equations modelling their operation are given in Table of Appendix D.

The demand response models produced generally indicate the amount of demand reductions the customer is willing to make [133]. Whilst it was assumed that customer would adhere to the demand response produced by the residential energy management systems the models produced by [133] give a fair indication of the extent to which the customer would allow the residential energy management system to make demand reductions within the household. Therefore comparing the demand response results in this chapter to the results produced by the demand response models published in [133] provides an opportunity for validating the generalised residential energy management system model.

Using the price and demand information from the dataset, the price elasticity of demand was found for each socio-demographic group paying a Time-Of-Use tariff. Price elasticity of demand is an economic measure that simply indicates how demand is expected to change with a change in price [133]. The formula for price elasticity of demand is given in Table of Appendix D. This price elasticity of demand was assumed to be the same for the customers paying a Flat-rate tariff. Using this information, the expected reduction in electricity use that each customer group is willing to make was calculated for each load type presented in Table of Appendix D. The average percentage reduction in electricity use was calculated for each group.

The results from past literature, the load models from [133], and the those obtained by the novel generalised residential energy management system model presented in this chapter was compared using a simple “Analysis of Variance” test [134]. “Analysis of Variance” is a test that compares the values obtained from different sources and returns a probability that the values are similar. This probability value (or p-value) must be less than a threshold for the values to be considered similar. The typical threshold value used for “Analysis of Variance” test is p-value < .05 [134]; that is, if the p-value of the test is less than 5% then the mean values being compared is less than 5% likely to be similar by chance. In a such a case the values being compared are similar and that similarity is considered significant [134].

In this research, the test returns a probability that the results obtained by the residential energy management systems model are different from the results obtained from past literature and the demand response models in Table of Appendix D. According to standard results for “Analysis of Variance” (ANOVA) tests, if the probability value from the test is less than 0.05 then there is a less than 5% chance that the results produced by the generalised model of the residential energy management system is different to those normally obtained in past literature and the results obtained by the economic models produced by authors of [133]. This provides strong evidence that the generalised model of the residential energy management system produces sound results.

3.7 Simulation results

The autoregressive integrated moving average models were found for each of the 36 average load profiles representing the socio-demographic groups under investigation. These results are shown in Table 3.8. Since the mean absolute percentage values are all less than 10%, the autoregressive integrated moving average models used to represent the load profiles in this research are a sufficiently accurate representation of the actual load, and imply that the results obtained from the generalised model of the residential energy management system would also be accurate.

Table 3.8. Autoregressive integrated moving average model used to represent each average load profile

Customer group	Flat-Rate Tariff		Time-of-Use Tariff	
	ARIMA model	MAPE	ARIMA model	MAPE
Lavish Lifestyles	ARIMA (2, 1, 2)	2.06 %	ARIMA (2, 1, 2)	3.12 %
City Sophisticates	ARIMA (2, 1, 2)	4.91 %	ARIMA (1, 1, 2)	8.90 %
Mature Money	ARIMA (2, 1, 2)	2.59 %	ARIMA (2, 1, 2)	4.61 %
Starting out	ARIMA (2, 1, 2)	1.97 %	ARIMA (2, 1, 2)	2.91 %
Executive Wealth	ARIMA (2, 1, 2)	1.21 %	ARIMA (2, 1, 2)	1.85 %
Not Private Households	ARIMA (2, 1, 2)	1.58 %	ARIMA (2, 1, 2)	2.56 %
Steady Neighbourhoods	ARIMA (1, 1, 2)	3.00 %	ARIMA (2, 1, 1)	4.60 %
Career Climbers	ARIMA (2, 1, 2)	1.72 %	ARIMA (2, 1, 2)	3.03 %
Successful Suburbs	ARIMA (2, 1, 1)	4.95 %	ARIMA (1, 1, 2)	7.33 %
Modest Means	ARIMA (1, 1, 2)	3.71 %	ARIMA (2, 1, 2)	6.58 %
Student life	ARIMA (2, 1, 2)	2.53 %	ARIMA (1, 1, 2)	5.94 %
Striving Families	ARIMA (2, 1, 2)	1.95 %	ARIMA (2, 1, 2)	3.71 %
Comfortable Seniors	ARIMA (2, 1, 2)	2.91 %	ARIMA (2, 1, 2)	6.02 %
Countryside Communities	ARIMA (2, 1, 2)	2.88 %	ARIMA (1, 1, 1)	5.15 %
Poorer Pensioners	ARIMA (1, 1, 2)	3.67 %	ARIMA (2, 1, 1)	7.11 %
Young Hardship	ARIMA (2, 1, 2)	4.93 %	ARIMA (2, 1, 2)	6.93 %
Difficult Circumstances	ARIMA (2, 1, 2)	1.61 %	ARIMA (1, 1, 2)	3.13 %
Struggling Estates	ARIMA (1, 1, 2)	5.23 %	ARIMA (2, 1, 1)	9.13 %

ARIMA = autoregressive integrated moving average
MAPE = mean absolute percentage error

After ascertaining the best autoregressive integrated moving average models for each of the 36 average load profiles, the percentage reduction in average demand and peak-to-average demand was determined. The percentage reduction in average demand is given in Table 3.9 and Table 3.10 for customers on a Flat-rate and Time-Of-Use tariff respectively.

From Table 3.9 and Table 3.10 it is clear that the percentage average demand (k_1) after reduction by the residential energy management systems varies according to socio-demographic group, the tariff and the operational objectives used by the device. This has three points of significance.

Very few studies have been done to compare different objectives amongst customer groups and determine which objectives produce the most optimal demand response. Most studies only assume a set of objectives and find the optimal demand response for those objectives. However the results in Table 3.9 and Table 3.10 illustrate the importance of comparing objectives and then selecting those that would produce the highest optimal demand response for a given customer group paying a given tariff type. For example, for customers classified as "Difficult Circumstances" the highest level of demand response can be obtained from these customers when they are paying a Flat-Rate tariff and the residential energy management systems installed in their homes operate to make electricity bills savings (see Table 3.9, scenario 2). On the other hand, for the "Countryside Communities" customer group, the highest level of demand response can be obtained when the customers are paying a Time-Of-Use tariff and the residential energy management systems installed in their home operates to produce electricity bills savings and tax savings (see Table 3.10, scenario 6). This implies that a one-size-fits-all approach for designing these devices cannot be taken when installing energy management systems on a large scale.

By understanding the interaction between socio-demographics, tariff and operational objectives, the retailer can influence the demand response that is needed from a customer group by simply changing the operational objectives of the device. This gives the impression that having a residential energy management system that can dynamically change objectives once instructed to by the retailer would have significant advantages when deploying these systems on a large scale.

Most research when modelling residential energy management systems quote both the tariff type and the operational objectives used to model the device. However, the studies seldom mention the socio-demographic profile of the customers that form the sample of their investigation. However, from Table 3.9 and Table 3.10 it is obvious that this is an important aspect for the research on residential energy management systems. The socio-demographics of customers does dictate the percentage reduction in average electricity that can be obtained from a residential energy management system.

The third point of significance is that when “increasing retail profit” objective was considered in the operation of the residential energy management systems (scenarios 9 to 16) less of a demand response was produced from customers paying both the Flat-rate and Time-Of-Use tariff. However, there was more stability, that is, less variation in the demand responses produced across the socio-demographic groups.

These points of significance suggest that the retailer needs to be very clear as to what their objective is in deploying these systems on a large scale. Selling these devices to customers without regard for which operational objective is used by the device or what tariff type the customer pays may produce unexpected results in terms of the average demand response that the retailer can expect from these devices.

Table 3.9. Forecasted percentage average demand (k_1) after demand response from customers paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9*	10*	11*	12*	13*	14*	15*	16*
Lavish Lifestyles	100.0	82.7	88.1	71.9	73.7	71.6	49.4	61.1	95.0	95.0	95.0	95.0	95.0	95.0	95.0	95.0
City Sophisticates	100.0	59.1	66.1	58.0	79.4	70.5	80.8	76.5	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Mature Money	100.0	76.9	64.3	51.4	82.9	69.6	65.7	72.0	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Starting out	100.0	81.0	65.0	20.6	72.0	74.6	80.0	61.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Executive Wealth	100.0	21.7	75.1	87.3	59.7	78.4	76.1	69.2	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Not Private Households	100.0	61.1	66.0	60.4	69.0	71.8	81.1	81.7	95.0	95.0	95.0	95.0	95.0	95.0	95.0	95.0
Steady Neighbourhoods	100.0	82.9	80.9	39.6	43.9	63.0	83.6	63.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Career Climbers	100.0	60.5	77.1	79.2	80.3	78.5	72.1	60.1	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Successful Suburbs	100.0	50.0	70.5	66.2	63.8	64.9	76.8	75.6	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Modest Means	100.0	24.4	46.2	73.9	62.9	59.9	61.7	82.1	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Student life	100.0	64.6	67.4	64.4	68.1	43.3	47.0	74.8	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Striving Families	100.0	60.6	71.8	59.2	84.1	80.0	55.6	80.8	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Comfortable Seniors	100.0	72.8	75.2	79.3	82.0	58.7	75.1	55.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Countryside Communities	100.0	71.1	46.7	55.2	82.1	74.1	46.2	69.2	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Poorer Pensioners	100.0	79.8	78.2	58.1	70.6	61.2	57.5	18.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Young Hardship	100.0	49.5	26.5	75.6	68.8	32.8	54.3	67.4	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Difficult Circumstances	100.0	23.3	25.1	54.1	53.9	60.7	59.6	60.0	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Struggling Estates	100.0	65.0	63.7	75.4	70.8	63.0	71.4	66.2	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Mean	100.0	60.4	64.1	62.8	70.4	65.4	66.3	66.5	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Variance	100.0	82.7	88.1	71.9	73.7	71.6	49.4	61.1	95.0	95.0	95.0	95.0	95.0	95.0	95.0	95.0

*Most of the values in this column only change after the 4th and 5th decimal places

Table 3.10 Forecasted percentage average demand (k_1) after demand response from customers paying a Time-Of-Use tariff

Customer group	Case															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	100.0	74.2	69.7	71.8	71.2	53.1	40.0	67.2	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
City Sophisticates	100.0	86.6	59.8	88.1	69.4	58.4	88.3	69.4	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Mature Money	100.0	67.2	60.7	63.5	64.4	68.4	59.6	71.7	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Starting out	100.0	88.9	61.1	60.9	81.0	50.4	56.0	35.0	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Executive Wealth	100.0	55.9	35.7	55.7	45.8	35.9	59.1	58.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Not Private Households	100.0	71.0	61.8	72.1	44.8	54.5	78.2	48.3	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Steady Neighbourhoods	100.0	69.1	45.6	75.4	78.9	67.0	62.9	79.3	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Career Climbers	100.0	66.8	69.8	67.3	52.9	66.9	86.7	71.3	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Successful Suburbs	100.0	70.4	55.5	71.0	79.9	60.5	76.4	60.0	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Modest Means	100.0	68.9	71.6	63.4	85.2	70.2	62.4	72.9	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Student life	100.0	62.4	82.4	73.4	61.9	78.2	77.7	74.0	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Striving Families	100.0	84.2	61.9	41.2	71.6	19.3	51.8	51.5	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Comfortable Seniors	100.0	75.1	64.8	37.8	67.6	68.3	67.9	63.6	94.7	94.7	94.7	94.7	94.7	94.7	94.7	94.7
Countryside Communities	100.0	56.2	53.3	70.5	63.3	43.8	67.2	64.6	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Poorer Pensioners	100.0	66.3	67.0	76.5	52.4	63.5	80.9	76.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Young Hardship	100.0	53.3	35.1	24.6	49.1	44.9	53.0	60.4	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Difficult Circumstances	100.0	72.1	51.9	45.5	74.9	29.3	78.0	67.6	94.9	94.9	94.9	94.9	94.9	94.9	94.9	94.9
Struggling Estates	100.0	71.3	43.0	70.4	61.1	78.8	44.7	52.6	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Mean	100.0	70.0	58.4	62.7	65.3	56.2	66.1	63.6	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8
Variance	100.0	74.2	69.7	71.8	71.2	53.1	40.0	67.2	94.8	94.8	94.8	94.8	94.8	94.8	94.8	94.8

*Most of the values in this column only change after the 4^{th} and 5^{th} decimal places

Table 3.11. Forecasted percentage peak-to-average demand (k_2) after demand response from customer groups paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	100.0	88.4	72.0	73.8	41.7	57.8	56.0	50.6	84.9	84.9	84.9	84.9	84.9	84.9	84.9	84.9
City Sophisticates	100.0	43.9	47.4	65.0	46.8	50.6	75.5	61.1	82.2	82.2	82.2	82.2	82.2	82.2	82.2	82.2
Mature Money	100.0	85.0	65.5	51.2	53.4	63.7	53.1	33.5	81.9	81.9	81.9	81.9	81.9	81.9	81.9	81.9
Starting out	100.0	53.3	49.6	39.3	96.5	58.4	75.0	44.8	87.0	87.0	87.0	87.0	87.0	87.0	87.0	87.0
Executive Wealth	100.0	27.9	39.1	91.7	40.0	37.4	50.0	20.3	83.7	83.7	83.7	83.7	83.7	83.7	83.7	83.7
Not Private Households	100.0	57.1	53.9	88.6	61.6	58.3	27.9	37.3	83.8	83.8	83.8	83.8	83.8	83.8	83.8	83.8
Steady Neighbourhoods	100.0	48.2	45.0	76.3	58.5	39.5	48.8	69.9	81.5	81.5	81.5	81.5	81.5	81.5	81.5	81.5
Career Climbers	100.0	64.0	35.7	27.2	12.5	53.8	93.1	72.1	83.6	83.6	83.6	83.6	83.6	83.6	83.6	83.6
Successful Suburbs	100.0	92.2	76.7	51.6	68.2	74.6	37.7	49.4	86.7	86.7	86.7	86.7	86.7	86.7	86.7	86.7
Modest Means	100.0	48.6	78.2	86.4	31.4	62.9	59.4	88.4	75.5	75.5	75.5	75.5	75.5	75.5	75.5	75.5
Student life	100.0	59.6	72.9	34.1	74.8	40.6	58.3	64.3	83.5	83.5	83.5	83.5	83.5	83.5	83.5	83.5
Striving Families	100.0	69.7	70.3	62.8	63.9	50.9	37.1	61.0	84.5	84.5	84.5	84.5	84.5	84.5	84.5	84.5
Comfortable Seniors	100.0	40.2	22.9	56.1	43.6	92.0	46.7	36.0	84.5	84.5	84.5	84.5	84.5	84.5	84.5	84.5
Countryside Communities	100.0	73.0	28.0	69.3	44.9	35.6	53.5	42.3	83.1	83.1	83.1	83.1	83.1	83.1	83.1	83.1
Poorer Pensioners	100.0	40.6	53.9	71.2	18.9	23.4	37.2	73.4	85.9	85.9	85.9	85.9	85.9	85.9	85.9	85.9
Young Hardship	100.0	50.1	41.6	31.8	60.9	50.2	55.9	61.7	85.9	85.9	85.9	85.9	85.9	85.9	85.9	85.9
Difficult Circumstances	100.0	40.5	30.7	62.6	32.5	44.6	82.0	15.6	85.2	85.2	85.2	85.2	85.2	85.2	85.2	85.2
Struggling Estates	100.0	50.1	48.7	74.0	59.7	86.0	40.2	29.6	86.3	86.3	86.3	86.3	86.3	86.3	86.3	86.3
Mean	100.0	57.4	51.8	61.8	50.5	54.5	54.8	50.6	83.9	83.9	83.9	83.9	83.9	83.9	83.9	83.9
Variance	100.0	88.4	72.0	73.8	41.7	57.8	56.0	50.6	84.9	84.9	84.9	84.9	84.9	84.9	84.9	84.9

Table 3.12. Forecasted percentage peak-to-average demand (k_2) after demand response from customer groups paying a Time-Of-Use tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	100.0	90.4	36.8	48.7	58.1	62.7	28.4	64.6	84.1	84.1	84.1	84.1	84.1	84.1	84.1	84.1
City Sophisticates	100.0	67.7	74.2	38.9	44.9	64.0	65.0	52.9	82.7	82.7	82.7	82.7	82.7	82.7	82.7	82.7
Mature Money	100.0	40.0	22.3	51.8	70.4	26.2	66.9	70.0	83.9	83.9	83.9	83.9	83.9	83.9	83.9	83.9
Starting out	100.0	56.2	62.6	37.5	56.9	88.6	43.0	72.6	83.5	83.5	83.5	83.5	83.5	83.5	83.5	83.5
Executive Wealth	100.0	42.2	70.6	52.7	71.0	32.1	48.7	40.0	84.5	84.5	84.5	84.5	84.5	84.5	84.5	84.5
Not Private Households	100.0	27.0	45.4	54.4	30.2	60.9	20.5	30.1	83.0	83.0	83.0	83.0	83.0	83.0	83.0	83.0
Steady Neighbourhoods	100.0	49.7	41.1	71.7	74.2	52.3	85.9	77.4	84.1	84.1	84.1	84.1	84.1	84.1	84.1	84.1
Career Climbers	100.0	54.7	75.4	94.1	46.7	46.8	62.5	5.4	83.9	83.9	83.9	83.9	83.9	83.9	83.9	83.9
Successful Suburbs	100.0	56.9	78.1	37.4	59.6	43.5	41.3	39.5	87.1	87.1	87.1	87.1	87.1	87.1	87.1	87.1
Modest Means	100.0	36.2	44.2	33.6	68.6	68.0	50.8	70.6	85.9	85.9	85.9	85.9	85.9	85.9	85.9	85.9
Student life	100.0	59.5	47.6	18.8	94.2	45.0	56.3	61.8	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
Striving Families	100.0	65.9	65.0	66.9	59.1	52.9	67.1	57.5	84.0	84.0	84.0	84.0	84.0	84.0	84.0	84.0
Comfortable Seniors	100.0	26.0	72.1	49.5	77.7	37.1	85.3	11.9	83.4	83.4	83.4	83.4	83.4	83.4	83.4	83.4
Countryside Communities	100.0	52.0	59.8	89.5	50.2	63.1	31.4	78.6	85.9	85.9	85.9	85.9	85.9	85.9	85.9	85.9
Poorer Pensioners	100.0	60.6	29.0	88.8	86.9	34.5	17.4	58.8	86.2	86.2	86.2	86.2	86.2	86.2	86.2	86.2
Young Hardship	100.0	44.2	52.4	50.9	26.3	54.1	67.0	61.8	84.1	84.1	84.1	84.1	84.1	84.1	84.1	84.1
Difficult Circumstances	100.0	59.3	52.4	73.6	74.6	35.8	91.2	70.0	81.9	81.9	81.9	81.9	81.9	81.9	81.9	81.9
Struggling Estates	100.0	74.1	50.4	52.3	22.3	69.9	53.8	53.4	85.6	85.6	85.6	85.6	85.6	85.6	85.6	85.6
Mean	100.0	53.5	54.4	56.2	59.5	52.1	54.6	54.3	84.5	84.5	84.5	84.5	84.5	84.5	84.5	84.5
Variance	100.0	90.4	36.8	48.7	58.1	62.7	28.4	64.6	84.1	84.1	84.1	84.1	84.1	84.1	84.1	84.1

To further illustrate this, Table 3.11 and Table 3.12 show that the percentage peak-to-average after demand reduction varies greatly according to tariff, socio-demographic and objective functions. For example, when looking at customers who fall under the "Successful Suburbs" socio-demographic group, the greatest percentage peak-to-average demand (k_2) after reduction for those paying a Flat-rate tariff occurs when the residential energy management systems work to produce tax and emissions savings (scenario 7, Table 3.11). In this case the peak-to-average demand after reduction is 37.7%. However, if that same group is considered when paying a Time-Of-Use tariff, then the optimal percentage peak-to-average demand (k_2) after reduction is obtained when these customers have residential energy management systems that work to produce electricity bill, tax and emissions savings (scenario 8, Table 3.12). In this case the peak-to-average demand after reduction is 39.5%. The implication here is that if these systems are installed on a large scale, they can be used to manage peak-to-average demand and consequently risk. However, as indicated earlier the retailer must be careful to match tariff and customer socio-demographics with appropriately designed residential energy management systems. If this is not done, then the risk experienced by customer groups can be made worse if the reduction in demand amongst different groups is not even.

Thus far, this work implies that the retailer does not necessarily need appliance level electricity consumption data to model and analyse the possible effects of the large-scale deployment of residential energy management systems. To illustrate the validity of the results, the range of values for the forecasted percentage reduction in average demand and peak-to-average demand found in past literature as well as demand response models shown in Table of Appendix D were compared to the results found in this work. The results of the comparison are given in Table 3.13.

Table 3.13. Comparing average and peak-to-average values different sources

Tariff Type	Load Profile change after demand response	Range of values found in this work	Range of values found in past literature	Range of Values found from demand response models
Flat-Rate	% of average demand (k_1) left after demand response	18.9 % to 95.0 %	14.7 % to 65.5 % [135]	69.2 % to 99.6 %
	% of average-to-peak demand (k_2) left after demand response	12.5 % to 96.5 %	25.0 % to 61.0 % [135]	14.7 % to 85.1 %
Time-Of-Use	% of average demand (k_1) left after demand Response	19.3 % to 94.9 %	7.0 % to 50.1 % [18]	69.2 % to 99.7 %
	% Reduction in average-to-peak demand (k_2) left after demand response	5.4 % to 94.2 %	46.0 % to 75.0 % [136]	8.8 % to 88.1 %

p-value < 0.05

The results show that the range of values in this work is comparable to those found past research papers and the models presented in Table of Appendix D. The p-value found where comparing the reduction values in all three sources was found to be 0.039. This value implies that the probability that the results agree by chance is less than 3.9%. This value is less than the threshold value of 5% and hence the results are considered significant. This means that the generalised residential energy management system model presented in this chapter produced valid results lending strong support for using load profile data to model the operation of these devices.

3.8 Discussion

The generalised residential energy management system model involved using a time series autoregressive integrated moving average model to forecast ahead the demand response of the system based on the operational objectives of the system. It is obvious at this point that the model can be used as a tool to strategically manage the large-scale deployment of residential energy management systems. However, there are several strengths and weakness that must be expressly mentioned.

The generalised residential energy management system model is based on an autoregressive integrated moving average model (Equation (3.4)). This model is used to forecast the expected percentage reduction in average and peak-to-average demand after demand response. The time series model also expressly quantifies the errors produced during the forecasting. This implies that the model can be used for strategic planning in demand response programs and becomes extremely useful for the retailer when deciding on hedging strategies for risk management. This model is also useful for the retailer when planning on appropriate incentives to pay customers for their demand response.

An ability to forecast is particularly useful for stakeholders in the Low Carbon London Project. One of the aims of the project was to use Low Carbon technologies to manage network constraints using real-time control, making it possible to defer or avoid network reinforcement. The forecasting capabilities of the model presented in this chapter would go a long way towards helping retailers who participate in such projects to achieve such goals.

Another strength is that the autoregressive integrated moving average model used to model the device can easily be replaced with any time series model. For example, if a greater emphasis needs to be placed on studying the financial outcomes of these devices, the autoregressive integrated moving average model can easily be replaced with a "Generalised Autoregressive Conditional Heteroskedasticity" model. This is a statistical time series model that can be used to analyse a number of different types of micro and macro-economic data [137].

As the model is independent of any physical device or any specific grid architecture its generalisability is another strength and makes the model versatile and adaptable to any research that involves studying the implementation of these devices on a large or small scale. Nevertheless, the model does have one weakness: the model treats the household like a black box, this means that the model does not give any details about the appliances in the home or how the reductions reflect changes in appliance schedules. This is why it was necessary to have a validation of the model results to ensure that the results in agreement with both demand response models in Table of Appendix D what obtains in the current state-of-the-art.

3.9 Concluding remarks

One of the major issues for residential energy management system modelling, until now, is that it relied heavily on disaggregated appliance data. Since large stores of disaggregated data are not available, it was necessary to develop a new model to study the large-scale implementation of these devices. The objective for this chapter, therefore, was to create a generalised model for residential energy management systems that was based solely on the aggregated demand profile of a household. The model involved using a time series model autoregressive integrated moving average to forecast the demand response of the system based on the operational objectives of the system.

The results of the model revealed that the percentage average and peak-to-average demand after reduction varies according to socio-demographic group, tariff type paid by customers and operational objectives used by the device. The results of the model were validated using results from previously published demand response models.

The one weakness of the model is that it treats the household like a black box and thus is unable to give details about the interaction between the residential energy management system and other household appliances that would produce the demand response illustrated. Nevertheless, the model lends itself to being used for strategic planning.

Chapter 4

Large-scale cost-benefit analysis for customer and retailer

4.1 Introduction

Having developed and validated a generalised model for residential energy management systems using the load profile of households a large-scale cost-benefit analyses of these devices can be done. However, one of the issues that has been established as pervading the current state-of-the-art is the uncertainty about the benefit of residential energy management systems to the customer and retailer. It is clear from the generalised model discussed in Chapter 3 that these devices can produce a demand response that is dependent on the socio-demographic of customers, the tariff type and the operational objectives of the device. Furthermore, it was postulated in the research discussed in Chapter 2 that these devices can influence other factors (such as customer diversity) that impact retail portfolios. Nevertheless, there has been very little in past literature to quantify and compare the customer and retail portfolio benefits derived from these devices across the three factors identified.

Such an analysis would also help the retailer and customer consider all options available to them in terms of device configurations (operational objectives of the device) and identify potential opportunities to maximise benefits. Moreover, an analysis of the direct and indirect cost and benefits of these devices can help the retailer make informed decisions especially in feasibility studies and demand response program development.

As such, this chapter has been dedicated to use the generalised residential energy management system model to examine how socio-demographic profile, tariff structures, and the choice of operational objectives of these devices, interact to influence their benefits for customers and portfolio outcomes for retailers.

4.2 Cost-benefit analysis done for the customer

A summary of the method used to simulate the cost-benefit of these devices for the customer is given in the flow chart Figure 4.1.

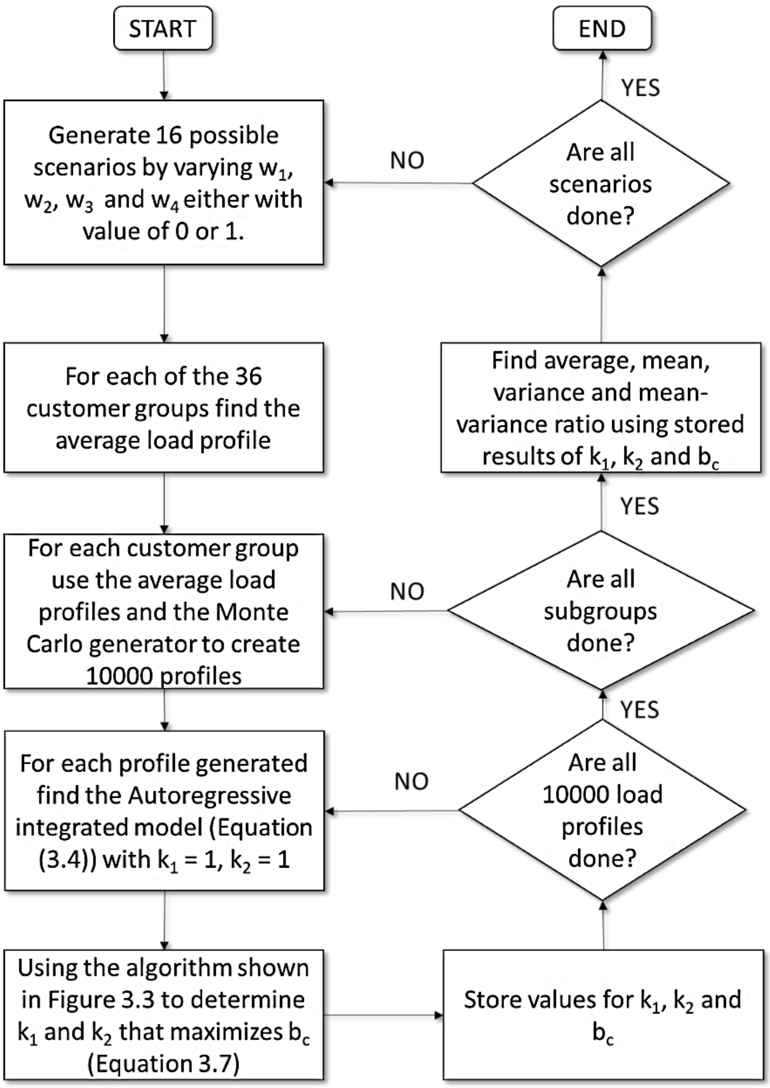


Figure 4.1. Flow chart for cost-benefit analysis for the customer

In accordance with the flow chart shown in Figure 4.1, the data from Chapter 3 was used to conduct a cost benefit analysis of the large-scale installation of residential energy management systems for the customer. To begin, the 36 average load profiles created for each representing each socio-demographic group (and tariff type) were paired with the generalised energy system model and subjected to a full-factorial analysis of variations to its objective function. These variations are as shown in Table of Appendix E.

Each scenario in Table of Appendix E was examined for each of the 36 subgroups created to understand how the benefits and cost of these devices vary with socio-demographic, tariff structure and combination of objective functions. The algorithm used is given in Table 3.7.

In accordance with the algorithm, 10,000 monthly electricity use profiles were generated by the Monte Carlo generator shown in Equation (3.10) for the first customer group (i.e., "Lavish Lifestyles" customers under a Flat-Rate tariff) using the group's average load profile. For each scenario shown in Table of Appendix E, the 10,000 load profiles generated were fed into the residential energy management system model to find 10,000 values for the optimal benefit-cost ratio (b_c), reduced forecasted average demand (k_1) and reduced forecasted peak-to-average demand (k_2) for the customer group. Using the 10,000 results the average benefit-cost ratio for the group was found. This was then repeated for the other 35 customer groups.

Furthermore, the mean, variance and mean-variance ratio for the benefit-cost across all customer groups for each scenario was found. The mean represents the average benefit-cost that a set of operating objectives would produce across all socio-demographic groups. The higher the mean, the better the objectives are for the customer groups. The variance represents the level of equity amongst the socio-demographic groups for a given set of operational objectives. The lower the variance, the more equitable the benefits and costs are across the different customer groups. The mean-variance ratio represents the mean benefit for every dollar of inequity amongst the customer groups for a given set of residential energy management systems operating objectives. The higher the mean-variance, the more suitable the given set of objective functions is for the residential energy management system.

4.3 Cost-benefit analysis done for the electricity retailer

4.3.1 Characterising customer diversity, retail profit and risk

For each customer group, diversity, retail profit and retail risk were characterised. Socio-demographic diversity was characterised using the Simpson Index [138]. The Simpson Index, Equation (4.1), was chosen because it is widely used, easy to calculate, can be adapted to different situations where diversity needs to be calculated [138] and considers the proportional contribution of each member of the group for the characteristic being measured. In the case of residential customers, the characteristic being measured is the amount of electricity consumed by each type of customer.

$$S_i = 1 - \sum_{i=1}^{N} \frac{s_h(s_h - 1)}{s_N(s_N - 1)} \tag{4.1}$$

where	
S_i	Customer diversity during hour i
s_h	Demand of household h during hour i
s_N	Aggregated demand of households during hour i
N	Total number of households

Once the customer diversity is known for every hour under consideration, the average customer diversity was found for the group of households. This method of calculating diversity accounted for the fact that the contribution of households to the aggregated demand of a group can change from hour to hour.

Furthermore, the average monthly amount paid for electricity by residential customers minus the cost of electricity on the wholesale market (the spot price) was used to determine the expected profit received by the retailer. From the data obtained, 4,286 households were under a flat-rate tariff of 0.14228 £/kWh and 1,093 households were under a three-tier Time-of-use tariff; high (0.69 £/kWh) medium (0.11 £/kWh) and low (0.033 £/kWh) rates. The change in average monthly profit made after installing residential energy management systems for electricity consumed was calculated using Equation (4.2).

$$P_m = \sum_{\mathrm{t}=1}^{T} d_t{}^*(r_t - s_t) \qquad (4.2)$$

where

P_m	Profit made from electricity consumed by household
r_i	Hourly retail tariff
s_t	Hourly spot price

Variance in the aggregated profit was used to assess the risk associated with profit received from the households [139].

4.3.2 Simulating the effects of the devices on the retail portfolio

A flow chart of the method used to simulate the effects of residential energy management systems on retail profit is shown in Figure 4.2.

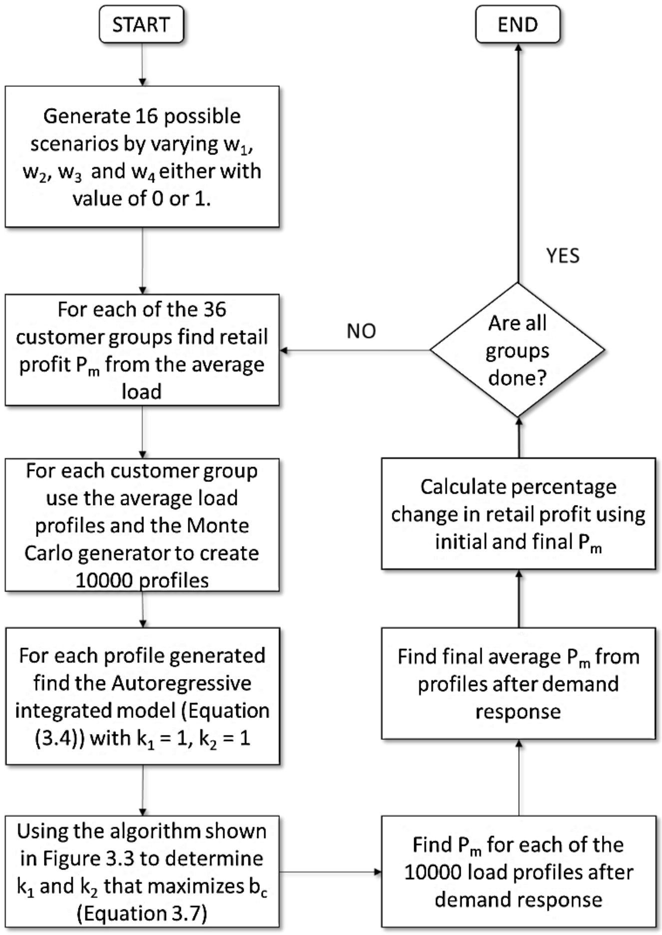


Figure 4.2. Flow chart for method used to simulate the effects of devices on retail profit

In accordance with Figure 4.2, each scenario in Table of Appendix E was examined for each of the 36 customer groups created in order to understand how the percentage change in expected retail portfolio profit varied with socio-demographic, tariff structure and the combination of objective functions. The algorithm used to do this is given in Table 4.1.

Table 4.1. Algorithm for generating optimal change in profit for retail portfolio

Algorithm Input: *Load profile data for all households*	
1	Find the representative average monthly load profile for the first household subgroup.
2	Convert into an autoregressive integrated moving average model (M_A)
3	Use the autoregressive integrated moving average equation to forecast 1 month ahead the average monthly load profile
4	Use Equation (4.2) to calculate the initial profit P_m from the forecast
5	Use the Monte Carlo generator (shown in Equation (3.10)) to generate 10000 load profiles from the representative average monthly load profile.
6	Use the algorithm given in Figure 3.3 to find the optimal reduced load profile of household, optimal values for k_1, k_2 and b_c for each of the 10 000 load profiles.
7	Find the average k_1, k_2 and b_c values from the 10 000 results and store the final averages.
8	Use the average k_1, $k_2$values in the initial autoregressive integrated moving average model (M_A) to forecast 1 month ahead the average monthly load profile
9	Use Equation (4.2) to calculate the final profit P_m from the forecast.
10	Calculate the percentage change in profit from the initial P_m to the final P_m.
11	Repeat steps 1 to 10 for the other 15 scenarios presented in Table of Appendix E.
12	Repeat steps 1 to 11 for the other 35 customer groups.
Algorithm Output: *576 average values change in profit of the households under different tariff types and scenarios for the operational objectives of the residential energy management system.*	

As indicated in the algorithm, the initial average household profit (P_m) associated with the average load profile was found for the first customer group (i.e., “Lavish Lifestyles” customers paying a Flat-Rate tariff). Then, 10,000 monthly electricity use profiles were generated using a Monte Carlo generator shown in Equation (3.10).

For each scenario shown in Table of Appendix E, the 10,000 load profiles generated were fed into the residential energy management system model to find 10,000 optimal load profiles. Using the 10,000 results, average values for the forecasted reductions in average (k_1) and peak-to-average (k_2) electricity use after demand response for the “Lavish Lifestyles” customers paying a Flat-Rate tariff was found. The final average household profit (P_m) associated with the load profile after demand response was found. The difference between the percentage change in P_m from the initial to the final average value was then calculated and stored. This was repeated for each socio-demographic group paying each tariff type.

Once profit was dealt with, the relationship between customer diversity and retail risk was explored. The flowchart of the method used to do this is given in Figure 4.3.

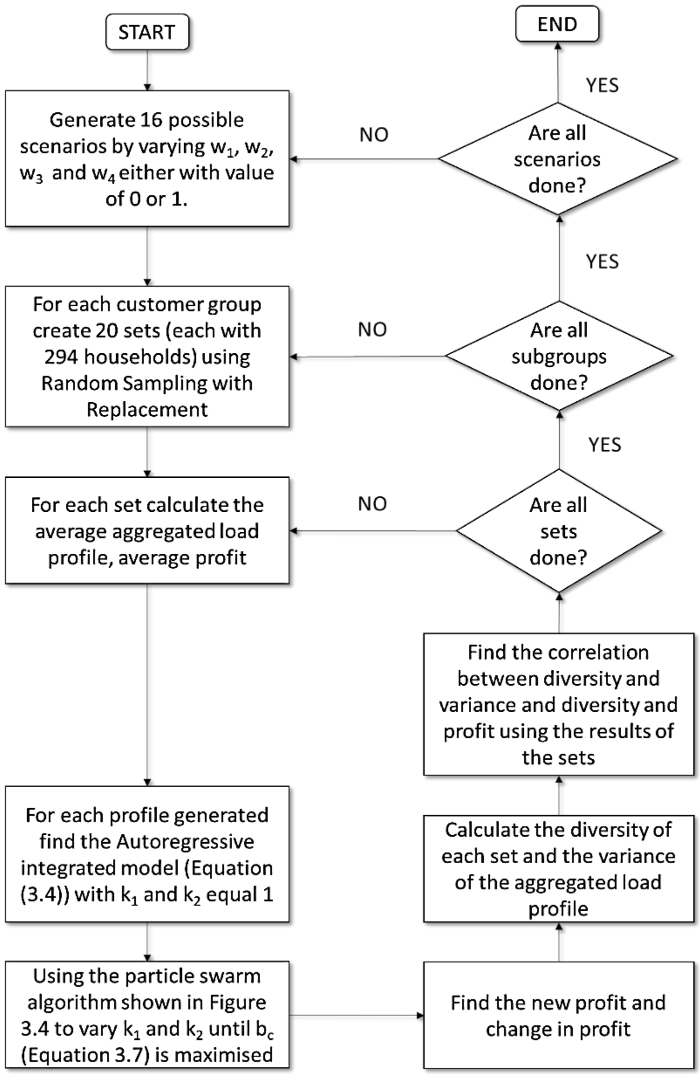


Figure 4.3. Flow chart for method used to calculate correlation between diversity, risk and profit

For the first subgroup (i.e., "Lavish Lifestyles" customers paying a Flat-Rate tariff), 20 sets of households were created. The number of households to include in each set was determined using a statistical table [141]. According to the parameters of this statistical table [141], in order to assess the relationship between customer diversity, profit and risk at a 95% confidence level, with a 5% margin of error, each set must have at least 291 households. Each set therefore, consisted of 291 households selected from the subgroup using a "Random Sampling with Replacement" [140] technique. The number of sets created from each subgroup was determined arbitrarily. Confidence level simply indicates how certain the results of the study are expected to be [141].

For each set the aggregated average monthly load profile was found and the diversity of the set was calculated using the Simpson Index, Equation (4.1). For the same sets, for each scenario of operational objectives shown in Table of Appendix E, the aggregated average monthly load profile was paired with the residential energy management system model and the optimal average aggregated load profile was obtained. The aggregated profit and risk from the optimal load profile were calculated and recorded. The steps of creating 20 sets, calculating diversity and aggregated average monthly load profile for each set, calculating profit and risk from the optimal load profile produced by the energy management devices for each case in Table of Appendix E, was repeated for the remaining 35 customer groups.

Thereafter, three other subgroups were created. Each subgroup consisted of 500 households selected using the “Random Sampling with Replacement” technique [140]. The number of households in each of the newly created subgroups was arbitrarily set. The first subgroup consisted of households that were subject to the Flat-rate tariff only without regard for socio-demographic group. The second subgroup consisted of households that were subject to the Time-of-Use tariff only again without regard for socio-demographic group. The third subgroup consisted of a mixture of households selected without regard for socio-demographic or tariff structure. The steps of creating 20 sets, calculating diversity and aggregated average monthly load profile for each set, calculating profit and risk from the optimal load profile produced by the energy management devices for each case in Table 3.6 was repeated for these three newly created groups.

Once results were obtained for each of the 20 sets in all 39 subgroups (the 36 original customer groups and the three newly created subgroups), a correlation analysis was done. Using the 20 sets from the first customer group, the correlation (Pearson’s Correlation Coefficient “ρ”) between the customer diversity and financial risk under each “scenario” of objectives for the residential energy management systems was found. This was repeated for each of the other 38 subgroups. This resulted in correlation values (ρ) for each of the operational objectives listed in Table 3.6 for each subgroup.

The "ρ" values produced provide an indicator of the strength of the relationship between the Simpson Index and variance in profit for each subgroup. If any of the "ρ" values is above 0.7, then this indicates a strong positive relationship between customer diversity and variance in retail profit [142]; that is, a high positive "ρ" value points to a high probability that as customer diversity increases the variance in profit received from the subgroup also increases for a given type of energy management system. Conversely, an "ρ" value below –0.7 indicates a strong negative relationship between the variables mentioned [142].

Finally, statistical software in MATLAB was used to determine the probability that the correlations values found are statistically significant. The lower the probability value (p-value) the more likely results are to be statistically significant. If the results are statically significant this means that the results were not obtained by chance or because of the sampling method used, but rather were inherent in the data. A p-value less than 0.05 is considered statistically significant [143].

4.4 Simulation results

4.4.1 Cost-benefit analysis for customer

Using the average load profiles of each of the 36 customer groups and the scenarios shown in Table 3.6 permitted the cost and benefit of the device for each customer group to be determined. The results are shown in Table 4.2 and Table 4.3. Each column represents the benefit-cost ratio for all groups if the residential energy management system operated with only one set of operational objectives; that is, if a one-size-fit-all approach is used. For example, column 9 (scenario 8) in Table 4.3 represented the benefit-cost ratio for the 18 customer groups under a Time-Of-Use tariff, if the residential energy management systems operated to increase customer bill savings, emissions savings, and tax savings.

There were values in Table 4.2 (cases 1, 9, 10, 12 and 16) and Table 4.3 (case 1) where the value of the cost-benefit appears to be zero. Case 1 for both Table 4.2 and Table 4.3 assumes that there is no residential energy management system in any household. Therefore, the cost-benefit from having no system installed is zero. In the other cases for Table 4.2 (case 9, 10, 12 and 16), rounding off the cost-benefit ratio to two decimal places lead to a zero result. This is a predictable result since in these cases the device works to maximise retail profit and not necessarily benefit the customer. This implies that such combination of objectives may not be useful for the customer.

In Table 4.2 and Table 4.3, the variance for the benefit-cost ratio for each set of operational objectives for the device is shown. The greater the variance the more inequitable the cost and benefits amongst customer groups. It was clear that there was an inequitable distribution of benefits and cost for every scenario. If there were an equitable distribution of benefits and cost, then for any given column the variance should be zero. However, there is no set of objectives that produces a variance of zero (excluding the trivial case shown in column 1 where no residential energy management systems are operating). This result is significant, as it shows that when one set of objectives is used for multiple customer groups the result is an inequitable distribution of benefits across the subgroups. Reflecting on this point, the greatest variance is found for “scenario 16” and the least variance is found for “scenario 2”. This means that there are some operational objectives that deliver a better overall outcome and more equitable distribution of cost and benefits for customers.

This becomes even clearer when the individual rows of Table 4.2 and Table 4.3 are considered. These show that there are some operational objectives that are more suitable for some customer groups than others. For example, it was clear that in Table 4.2 for “Steady

Neighbourhoods”, scenario 7 produced the largest benefit for the group (this case is where the residential energy management system operates to achieve emissions and tax savings). However, for “Career Climbers”, scenario 8 (where the device is operated to achieve electricity bill, emissions and tax savings) produces the largest benefit. Clearly socio-demographic profile should be considered when deciding the operational objectives used to operate residential energy management systems.

Moreover, the last row of Table 4.2 and Table 4.3 gives the mean-variance of each objective. The mean-variance simply indicates the average benefit-cost for every dollar of inequity produced between the groups. The higher this value, the better suited the combination of objectives is for all customer groups.

Table 4.2. Cost-benefit metric for customer groups paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.00	2.00	2.00	1.59	3.00	3.00	2.59	3.00	0.00	0.00	0.47	0.00	0.51	0.00	0.51	0.00
City Sophisticates	0.00	1.53	1.49	1.43	2.49	2.35	2.42	2.67	0.00	0.00	0.30	0.00	0.33	0.00	0.33	0.00
Mature Money	0.00	1.51	1.30	1.51	2.41	2.42	2.57	2.64	0.00	0.00	0.33	0.00	0.37	0.00	0.37	0.00
Starting out	0.00	1.55	1.90	1.71	2.50	2.39	3.00	2.95	0.00	0.00	0.33	0.00	0.37	0.00	0.37	0.00
Executive Wealth	0.00	1.49	1.50	1.30	2.35	2.24	2.30	2.49	0.00	0.00	0.25	0.00	0.28	0.00	0.28	0.00
Not Private Households	0.00	1.43	1.29	1.56	2.45	2.42	2.26	2.58	0.00	0.00	0.08	0.00	0.09	0.00	0.09	0.00
Steady Neighbourhoods	0.00	1.47	1.59	1.37	2.33	2.35	2.48	2.35	0.00	0.00	0.27	0.00	0.30	0.00	0.30	0.00
Career Climbers	0.00	1.61	1.36	1.54	2.61	2.34	2.41	2.51	0.00	0.00	0.30	0.00	0.33	0.00	0.33	0.00
Successful Suburbs	0.00	1.19	1.33	1.76	2.41	2.22	2.41	2.47	0.00	0.00	0.16	0.00	0.18	0.00	0.18	0.00
Modest Means	0.00	1.16	1.39	1.66	2.46	2.24	2.68	2.50	0.00	0.00	0.32	0.00	0.35	0.00	0.35	0.00
Student life	0.00	1.27	1.40	1.45	2.29	2.29	2.40	2.39	0.00	0.00	0.16	0.00	0.18	0.00	0.18	0.00
Striving Families	0.00	1.14	1.51	1.65	2.20	2.28	2.57	2.38	0.00	0.00	0.17	0.00	0.19	0.00	0.19	0.00
Comfortable Seniors	0.00	1.66	1.31	1.65	2.26	2.27	2.45	2.35	0.00	0.00	0.16	0.00	0.19	0.00	0.19	0.00
Countryside Communities	0.00	1.26	1.22	1.35	2.46	2.31	2.50	2.33	0.00	0.00	0.06	0.00	0.08	0.00	0.08	0.00
Poorer Pensioners	0.00	1.39	1.36	1.29	2.27	2.53	2.24	2.51	0.00	0.00	0.07	0.00	0.09	0.00	0.09	0.00
Young Hardship	0.00	1.18	1.13	1.31	2.23	2.17	2.34	2.38	0.00	0.00	0.06	0.00	0.08	0.00	0.08	0.00
Difficult Circumstances	0.00	1.45	1.16	1.41	2.37	2.19	2.17	2.34	0.00	0.00	0.05	0.00	0.07	0.00	0.07	0.00
Struggling Estates	0.00	1.32	1.26	1.48	2.37	2.12	2.31	2.47	0.00	0.00	0.30	0.00	0.33	0.00	0.33	0.00
Mean	0.00	1.42	1.42	1.50	2.42	2.34	2.45	2.52	0.00	0.00	0.21	0.00	0.24	0.00	0.24	0.00
Variance	0.00	0.05	0.05	0.02	0.03	0.04	0.04	0.04	0.00	0.00	0.01	0.00	0.02	0.00	0.02	0.00
Mean-Variance	0.00	30.54	27.28	68.72	74.13	63.05	66.08	66.26	0.00	0.00	14.33	0.00	14.44	0.00	14.44	0.00

Table 4.3. Cost-benefit metric for customer groups paying a Time-Of-Use tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.00	1.73	1.52	1.77	2.93	2.56	2.95	2.76	1.00	1.00	0.98	1.00	0.98	1.00	0.98	1.00
City Sophisticates	0.00	1.48	1.94	1.81	2.60	2.49	2.56	2.74	0.95	0.95	1.00	0.95	1.00	0.95	1.00	0.95
Mature Money	0.00	1.35	1.33	2.00	2.45	2.24	2.50	2.26	0.54	0.54	0.41	0.54	0.41	0.54	0.41	0.54
Starting out	0.00	1.35	1.63	1.57	2.39	2.59	2.69	2.74	0.63	0.63	0.98	0.63	0.98	0.63	0.98	0.63
Executive Wealth	0.00	1.30	1.19	1.18	2.37	2.27	2.49	2.33	0.49	0.49	0.39	0.49	0.39	0.49	0.39	0.49
Not Private Households	0.00	1.39	1.44	1.55	2.28	2.33	2.47	2.29	0.39	0.39	0.25	0.39	0.25	0.39	0.25	0.39
Steady Neighbourhoods	0.00	1.34	1.53	1.36	2.24	2.38	2.51	2.51	0.45	0.45	0.16	0.45	0.16	0.45	0.16	0.45
Career Climbers	0.00	1.34	1.63	1.61	2.40	2.32	2.71	2.35	0.56	0.56	0.63	0.56	0.63	0.56	0.63	0.56
Successful Suburbs	0.00	1.25	1.33	1.34	2.27	2.40	2.51	2.39	0.46	0.46	0.30	0.46	0.30	0.46	0.30	0.46
Modest Means	0.00	1.53	1.20	1.17	2.47	2.29	2.34	2.33	0.55	0.55	0.67	0.55	0.66	0.55	0.66	0.55
Student life	0.00	1.71	1.77	1.84	2.36	2.27	2.45	2.30	0.44	0.44	0.45	0.44	0.45	0.44	0.45	0.44
Striving Families	0.00	1.25	1.27	1.27	2.29	2.24	2.61	2.35	0.54	0.54	0.30	0.54	0.30	0.54	0.30	0.54
Comfortable Seniors	0.00	1.52	1.35	1.27	2.59	2.22	2.56	2.37	0.70	0.70	0.81	0.70	0.80	0.70	0.80	0.70
Countryside Communities	0.00	1.44	1.39	1.52	2.29	2.10	2.53	2.36	0.42	0.42	0.29	0.42	0.29	0.42	0.29	0.42
Poorer Pensioners	0.00	1.68	1.13	1.36	2.31	2.26	2.28	2.51	0.32	0.32	0.15	0.32	0.15	0.32	0.15	0.32
Young Hardship	0.00	1.00	1.00	1.00	2.00	2.00	2.00	2.00	0.22	0.22	0.00	0.22	0.00	0.22	0.00	0.22
Difficult Circumstances	0.00	1.06	1.15	1.04	2.27	2.17	2.20	2.24	0.29	0.29	0.27	0.29	0.27	0.29	0.27	0.29
Struggling Estates	0.00	1.38	1.43	1.46	2.53	2.39	2.43	2.71	0.57	0.57	0.61	0.57	0.61	0.57	0.61	0.57
Mean	0.00	1.39	1.40	1.45	2.39	2.31	2.49	2.42	0.53	0.53	0.48	0.53	0.48	0.53	0.48	0.53
Variance	0.00	0.04	0.06	0.08	0.04	0.02	0.04	0.04	0.04	0.04	0.09	0.04	0.09	0.04	0.09	0.04
Mean-Variance	0.00	35.56	24.41	18.10	62.68	105.41	58.40	56.83	12.94	12.94	5.10	12.94	5.11	12.94	5.11	12.94

For example, "scenario 5" has the highest mean-variance benefit-cost for all the groups on a Flat-Rate (74.13) tariff regime, whilst case 6 had the highest mean-variance for the socio-demographic groups under the Time-Of-Use (20.06) tariff regime. This means that the electricity provider needs to be careful if they adopt a one-size-fits-all approach to the large-scale deployment of residential energy management systems. If care is not taken in deciding the operational objectives for the device, the provider may not necessarily maximise the social welfare of all its customers.

Moreover, when comparing the overall mean-variance (i.e., the sum of the mean-variance values) for Table 4.2 and Table 4.3, the overall mean-variance is higher for a flat-rate tariff (175.07) and for Time-Of-Use tariff (103.02). This indicates that, in general, the tariff regime also needs to be given serious consideration when deciding the design of residential energy management systems.

4.4.2 Cost-benefit analysis for retailer

Having followed the method, Table 4.4 and Table 4.5 show the percentage change in profit experienced by a retailer resulting from the large-scale deployment of residential energy management systems. Clearly the change in profit depends heavily on the operational objectives used for these devices. In "scenario 1" when there are no energy management systems operating in the households, the change in retail profit is obviously zero. However, in "scenario 2" to "scenario 8" for both Table 4.4 and Table 4.5, the retailer experiences a negative change in profit; that is, with these combinations of objectives, the retailer loses profit. In Table 4.4, where households are under the Flat-Rate tariff regime, the average loss of profit ranged from –37.36 % (in scenario 8) to –28.58 % (in scenario 3). In Table 4.5, where households are under the Time-Of-Use tariff regime, the average loss of profit ranges from –42.56 (in scenario 6) to –32.12 (in scenario 4). Time-of-Use appears to result in a higher loss of profit for the first

8 cases of operational objectives. This is perhaps because the average Time-Of-Use rate is greater than the average Flat-rate. The average Time-Of-Use rate is 0.2765 £/kWh (this is the average of the unit rates) and the average Flat-rate is 0.14228 £/kWh. Therefore, a reduction in demand would result in more loss of profit for the retailer for customers paying a Time-Of-Use tariff.

Nevertheless, when “scenario 9” to “scenario 16” were examined (in both Table 4.4 and Table 4.5) there was an increase in profit associated with these combinations of operational objectives. The increase in profit is attributed to the fact that, in each of the cases from “scenario 9” to “scenario 16”, “increasing retail profit” was included in the objectives used to operate the energy management systems (as shown in Table 4.4). However, it was noted that the average increase in profit obtained from these devices was twice as high (at 0.36%) for household under the Time-Of-Use tariff as for households under the Flat-Rate tariff (at 0.18%). This result is expected since Time-Of-Use is designed to favour shifts in demand that can lead to an increase in retail profit.

These results settle the debate over whether profit can be made from the large-scale deployment of residential energy management systems; simply put, it depends on the combination of operational objectives used and the tariff customers pay. It is also worth noting that the amount of profit that can be lost (as seen from “scenario 2” to “scenario 8” in both Table 4.4 and Table 4.5) is greater than the increase in profit that can be made from the systems (as seen from “scenario 9” to “scenario 16” in both tables). This implies that the retailer must be very astute in deciding the operational objectives used to operate these systems on a large scale in order to avoid profit losses.

Table 4.4. Forecasted percentage change in profit from customer groups paying a Flat-rate tariff

Customer group	Case															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.00	-16.66	-34.08	-42.36	-18.88	-6.45	-16.13	-15.45	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
City Sophisticates	0.00	-49.09	-37.31	-38.92	-29.40	-44.84	-20.09	-15.94	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
Mature Money	0.00	-39.72	-24.13	-21.52	-34.17	-30.85	-34.57	-38.77	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Starting out	0.00	-29.15	-45.87	-15.84	-50.44	-39.45	-90.12	-28.02	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
Executive Wealth	0.00	-25.88	-39.60	-30.44	-32.94	-23.57	-23.20	-15.02	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19
Not Private Households	0.00	-41.88	-42.55	-32.87	-23.16	-23.19	-52.63	-23.84	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Steady Neighbourhoods	0.00	-35.13	-28.68	-24.74	-26.00	-21.95	-38.42	-47.73	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
Career Climbers	0.00	-37.78	-20.56	-49.50	-12.67	-54.51	-20.64	-18.13	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
Successful Suburbs	0.00	-36.81	-36.63	-31.74	-41.40	-29.44	-35.39	-51.51	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22
Modest Means	0.00	-22.51	-35.33	-33.08	-23.19	-31.95	-9.61	-22.23	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Student life	0.00	-45.46	-42.87	-31.14	-28.81	-43.53	-17.37	-16.42	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Striving Families	0.00	-31.27	-45.05	-38.55	-36.37	-38.12	-38.79	-24.56	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16
Comfortable Seniors	0.00	-40.39	-44.13	-28.69	-40.84	-23.77	-53.07	-32.50	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Countryside Communities	0.00	-42.94	-74.66	-23.75	-44.84	-26.79	-39.48	-54.74	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
Poorer Pensioners	0.00	-56.32	-25.16	-17.08	-24.98	-37.05	-54.04	-21.70	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
Young Hardship	0.00	-35.12	-33.13	-42.06	-39.40	-29.72	-34.41	-47.40	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46
Difficult Circumstances	0.00	-18.31	-34.96	-54.11	-68.73	-50.36	-38.73	-29.14	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Struggling Estates	0.00	-27.51	-27.70	-14.25	-35.40	-32.72	-36.61	-11.32	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Mean	0.00	-35.11	-37.36	-31.70	-33.98	-32.68	-36.29	-28.58	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Variance	0.00	-36.19	-37.55	-31.07	-34.87	-34.22	-37.48	-29.35	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18

Table 4.5. Forecasted percentage change in profit from customer groups paying a Time-Of-Use tariff

Customer group	Case															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.00	-9.79	-36.60	-12.40	-37.74	-37.97	-21.06	-22.20	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44
City Sophisticates	0.00	-7.56	-47.79	-14.25	-21.77	-35.40	-18.84	-27.98	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47
Mature Money	0.00	-25.70	-39.52	-48.58	-39.74	-48.66	-29.03	-44.77	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36
Starting out	0.00	-23.57	-25.89	-18.23	-49.03	-39.86	-45.81	-49.14	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37
Executive Wealth	0.00	-35.22	-26.87	-24.37	-37.51	-16.52	-52.90	-54.94	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
Not Private Households	0.00	-34.32	-37.58	-38.27	-14.79	-36.01	-60.94	-50.49	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
Steady Neighbourhoods	0.00	-39.91	-25.44	-20.95	-24.29	-24.43	-39.39	-62.81	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33
Career Climbers	0.00	-30.73	-27.14	-46.68	-23.71	-49.17	-26.72	-16.42	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38
Successful Suburbs	0.00	-30.78	-39.79	-41.44	-42.06	-35.71	-47.86	-46.95	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33
Modest Means	0.00	-54.96	-43.42	-23.01	-46.97	-45.87	-24.00	-46.19	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42
Student life	0.00	-51.04	-21.38	-41.31	-23.63	-38.82	-40.20	-18.08	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
Striving Families	0.00	-69.42	-23.11	-21.17	-21.95	-36.19	-38.40	-27.74	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
Comfortable Seniors	0.00	-49.54	-49.58	-27.40	-48.75	-54.82	-30.36	-31.70	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57
Countryside Communities	0.00	-19.31	-52.45	-22.54	-45.46	-26.08	-40.99	-24.06	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
Poorer Pensioners	0.00	-19.92	-49.01	-29.01	-28.29	-77.30	-52.64	-38.94	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Young Hardship	0.00	-46.88	-56.39	-74.97	-47.00	-49.67	-51.73	-54.32	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37
Difficult Circumstances	0.00	-44.44	-41.71	-42.52	-61.73	-76.62	-46.99	-40.00	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
Struggling Estates	0.00	-32.90	-22.42	-31.10	-22.24	-37.09	-50.97	-19.18	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36
Mean	0.00	-34.78	-37.00	-32.12	-35.37	-42.56	-39.93	-37.55	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36
Variance	0.00	260.31	130.48	238.19	171.41	246.59	154.27	208.75	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Aside from profit, the relationship between customer diversity and retail risk was also investigated with the results being shown in Table 4.6 to Table 4.7. Correlation values less than –0.700 and statistically significant (p-value less than 0.05) are highlighted in grey. In Table 4.6 the first column represents the relationship between socio-demographic diversity and retail financial risk (variance in revenue received from customers) when no energy management devices are operating. The average correlation for the first column in Table 4.6 was found to be –0.766. This means that on average, across the socio-demographic groups, as the diversity of customers increases, the financial risk associated with the revenue received from the customers decreases. The converse is also true; as customer diversity decreases, risk increases.

However, it can clearly be seen that from "scenario 2" to "scenario 8" in Table 4.6 that the addition of residential energy management systems weakens the relationship between socio-demographic diversity and financial risk as the average correlation values from "scenario 2" (–0.531) to "scenario 8" (–0.580) show. Nevertheless, in "scenario 9" to "scenario 16" when the objective "increasing retail profit" was included, the negative correlation between socio-demographic diversity and financial risk was strengthened once again.

These results call attention to the fact that residential energy management systems not only reduce peak-to-average electricity use (as is largely cited in the literature) but these systems also influence how other factors (such as customer diversity) affect retail risk. For example, if the retailer does not have a diverse group of customers under a Flat-rate tariff and wants to ensure that the lack of diversity does not increase financial risk, then deploying these devices with the appropriate operational objectives will have the dual effect of reducing risk by reducing peak-to-average electricity use and mitigating the effects of reduced customer diversity.

Table 4.6. Correlation between customer diversity and retail risk from customer groups paying a Flat-Rate tariff

Customer group	Case															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	-0.607	-0.385	-0.563	-0.344	-0.155	-0.724	-0.776	-0.392	-0.443	-0.752	-0.752	-0.340	-0.645	-0.770	-0.853	-0.724
City Sophisticates	-0.551	-0.552	-0.450	-0.058	-0.267	-0.224	-0.242	-0.549	-0.882	-0.685	-0.588	-0.571	-0.528	-0.723	-0.439	-0.667
Mature Money	-0.829	-0.165	-0.749	0.143	-0.801	-0.503	-0.578	-0.436	-0.905	-0.862	-0.798	-0.807	-0.821	-0.640	-0.829	-0.717
Starting out	-0.675	-0.249	-0.581	-0.595	-0.673	-0.251	-0.383	-0.382	-0.566	-0.572	-0.377	-0.634	-0.783	-0.814	-0.792	-0.819
Executive Wealth	-0.838	-0.812	-0.947	-0.745	-0.730	-0.788	-0.794	-0.723	-0.890	-0.910	-0.922	-0.945	-0.846	-0.727	-0.862	-0.897
Not Private Households	-0.649	-0.575	-0.539	-0.664	-0.568	-0.332	-0.713	-0.474	-0.814	-0.882	-0.694	-0.816	-0.742	-0.897	-0.708	-0.644
Steady Neighbourhoods	-0.738	-0.393	-0.527	-0.462	0.019	-0.507	-0.520	-0.774	-0.750	-0.875	-0.560	-0.812	-0.747	-0.571	-0.654	-0.883
Career Climbers	-0.653	-0.505	-0.780	-0.601	0.103	-0.660	-0.456	-0.775	-0.851	-0.738	-0.791	-0.781	-0.777	-0.853	-0.871	-0.796
Successful Suburbs	-0.648	-0.392	-0.401	-0.037	-0.576	-0.595	-0.680	-0.201	-0.409	-0.493	-0.721	-0.780	-0.869	-0.672	-0.564	-0.403
Modest Means	-0.768	-0.538	-0.691	-0.890	-0.497	-0.679	-0.679	-0.672	-0.921	-0.774	-0.906	-0.899	-0.946	-0.680	-0.903	-0.586
Student life	-0.802	-0.547	-0.286	-0.644	-0.368	-0.568	-0.762	-0.405	-0.877	-0.691	-0.822	-0.869	-0.925	-0.921	-0.699	-0.766
Striving Families	-0.800	-0.439	-0.736	-0.724	-0.832	-0.883	-0.831	-0.752	-0.865	-0.842	-0.852	-0.764	-0.870	-0.881	-0.870	-0.817
Comfortable Seniors	-0.810	-0.671	-0.580	-0.464	-0.890	-0.801	-0.709	-0.605	-0.823	-0.794	-0.802	-0.729	-0.756	-0.847	-0.810	-0.828
Countryside Communities	-0.754	-0.596	-0.711	-0.509	-0.274	-0.211	-0.297	-0.472	-0.809	-0.833	-0.459	-0.854	-0.926	-0.777	-0.864	-0.820
Poorer Pensioners	-0.891	-0.437	-0.724	-0.175	-0.458	-0.642	-0.784	-0.412	-0.740	-0.884	-0.824	-0.788	-0.834	-0.821	-0.853	-0.836
Young Hardship	-0.973	-0.763	-0.919	-0.814	-0.926	-0.913	-0.837	-0.822	-0.956	-0.941	-0.979	-0.974	-0.977	-0.969	-0.972	-0.968
Difficult Circumstances	-0.920	-0.864	-0.441	-0.502	-0.826	-0.840	-0.501	-0.782	-0.926	-0.897	-0.807	-0.732	-0.856	-0.903	-0.917	-0.726
Struggling Estates	-0.889	-0.683	-0.759	-0.454	-0.608	-0.305	-0.159	-0.814	-0.761	-0.817	-0.930	-0.750	-0.852	-0.836	-0.871	-0.752
Mean	-0.766	-0.531	-0.632	-0.474	-0.518	-0.579	-0.594	-0.580	-0.788	-0.791	-0.755	-0.769	-0.817	-0.795	-0.796	-0.758
Variance	0.014	0.034	0.031	0.081	0.095	0.054	0.045	0.036	0.026	0.014	0.027	0.021	0.012	0.012	0.018	0.017

Values highlighted in grey indicate strong statistically significant negative correlation

Table 4.7. Correlation between customer diversity and retail risk from customer groups paying a Time-Of-Use tariff

Customer group	Case															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	-0.538	-0.039	-0.444	-0.244	-0.290	0.022	-0.088	-0.361	-0.354	-0.446	-0.440	-0.686	-0.209	-0.353	-0.509	-0.393
City Sophisticates	-0.987	-0.609	-0.603	-0.385	-0.654	-0.792	-0.621	-0.697	-0.981	-0.990	-0.990	-0.988	-0.986	-0.980	-0.987	-0.997
Mature Money	-0.720	-0.204	0.022	-0.452	-0.101	-0.071	-0.064	-0.379	-0.537	-0.175	-0.124	-0.182	-0.231	-0.760	-0.354	-0.396
Starting out	-0.245	0.049	-0.271	-0.435	-0.453	0.371	-0.312	-0.227	-0.208	-0.257	-0.260	-0.272	-0.208	-0.145	0.074	-0.313
Executive Wealth	-0.452	-0.094	-0.481	-0.467	-0.328	-0.367	-0.293	-0.318	-0.389	-0.312	-0.045	-0.422	-0.063	0.073	-0.509	-0.354
Not Private Households	-0.088	-0.161	-0.190	-0.219	-0.169	-0.237	-0.428	-0.141	-0.222	-0.798	-0.398	-0.266	-0.246	-0.560	-0.444	-0.536
Steady Neighbourhoods	-0.766	-0.340	-0.531	-0.751	-0.089	-0.662	-0.690	-0.536	-0.343	-0.708	-0.299	-0.527	-0.372	-0.334	-0.751	-0.491
Career Climbers	-0.466	-0.586	0.010	-0.110	-0.400	-0.282	0.013	0.069	-0.357	-0.437	0.173	0.092	-0.004	0.389	-0.238	-0.329
Successful Suburbs	-0.447	0.213	-0.458	-0.107	0.087	-0.364	-0.127	-0.467	-0.117	-0.553	-0.271	-0.505	-0.681	-0.625	-0.635	-0.242
Modest Means	-0.697	-0.568	-0.457	-0.717	-0.122	-0.209	-0.125	-0.297	-0.513	-0.238	-0.208	-0.489	-0.770	0.030	-0.693	-0.493
Student life	-0.554	0.074	-0.181	-0.319	-0.195	0.119	-0.584	-0.432	-0.351	-0.579	-0.203	-0.721	-0.756	-0.689	-0.542	-0.549
Striving Families	-0.860	-0.725	-0.725	-0.794	-0.542	-0.200	-0.581	-0.214	-0.717	-0.803	-0.701	-0.836	-0.703	-0.708	-0.817	-0.768
Comfortable Seniors	-0.641	-0.244	-0.152	-0.845	-0.619	-0.254	-0.419	-0.662	-0.580	-0.619	-0.706	-0.709	-0.599	-0.664	-0.753	-0.685
Countryside Communities	-0.682	-0.368	-0.113	0.107	0.051	-0.297	-0.031	-0.196	-0.574	-0.214	0.013	-0.136	-0.229	-0.320	0.045	-0.121
Poorer Pensioners	-0.160	-0.189	-0.310	-0.181	-0.390	-0.117	-0.302	-0.436	-0.358	-0.364	-0.423	-0.465	0.144	-0.273	-0.617	-0.546
Young Hardship	-0.225	0.013	-0.465	0.062	-0.142	-0.220	-0.018	0.198	0.116	0.065	-0.340	-0.004	-0.098	0.483	-0.249	-0.341
Difficult Circumstances	-0.288	0.079	-0.074	-0.119	0.037	-0.486	0.213	-0.338	-0.335	0.019	-0.062	-0.422	0.067	-0.456	-0.754	0.147
Struggling Estates	-0.177	-0.042	-0.448	-0.375	-0.216	-0.680	-0.218	-0.373	-0.264	-0.419	-0.374	-0.628	-0.431	-0.426	-0.352	-0.395
Mean	-0.500	-0.208	-0.326	-0.353	-0.252	-0.262	-0.260	-0.323	-0.394	-0.435	-0.314	-0.454	-0.354	-0.351	-0.505	-0.433
Variance	0.068	0.075	0.047	0.081	0.050	0.081	0.065	0.050	0.058	0.081	0.079	0.083	0.107	0.156	0.083	0.062

Values highlighted in grey indicate strong statistically significant negative correlation

Table 4.8. Correlation between customer diversity and profit for mixed customer groups

Customer group	Case															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Group 1 (Flat-Rate)	-0.932	-0.748	-0.612	-0.825	-0.813	-0.471	-0.567	-0.892	-0.679	-0.908	-0.919	-0.940	-0.693	-0.799	-0.818	-0.845
Group 2 (Time-Of-Use)	-0.386	0.005	-0.095	-0.317	-0.032	-0.479	-0.618	-0.547	-0.362	0.330	-0.255	-0.265	-0.523	-0.174	-0.435	-0.052
Group 3 (Mixed Tariff)	-0.887	-0.637	-0.917	-0.853	-0.858	-0.821	-0.728	-0.716	-0.850	-0.874	-0.786	-0.778	-0.902	-0.665	-0.810	-0.844

Values highlighted in grey indicate strong statistically significant negative correlation

Nevertheless, the results for Table 4.7 paint a very different picture. For customers under a Time-Of-Use tariff, there is a very weak negative relationship between customer diversity and financial risk across most customer groups. This can clearly be seen from the average correlation values at the bottom of Table 4.7. The average correlation values range from –0.500 (scenario 2) to –0.252 (scenario 5). There is no discernible pattern of correlation values across the customer groups or across the "scenario" in Table 4.7. The dominant factor that appears to be affecting the correlation between customer diversity and financial risk is the tariff used by these households. It appears that under Time-Of-Use tariff, for the most part, customer diversity does not have a significant impact on financial risk for most customer groups. This means that tariff type can also be used to influence the relationship between customer diversity and financial risk.

The effects of tariff type become even more obvious in Table 4.8. For the mixed group of households under the Flat-rate tariff, the correlation between socio-demographic diversity and financial risk was strongly negative (correlation below –0.700) for most combinations of operational objectives for residential energy management systems. For some of the other objectives the correlation is weak to moderately strong (that is, between –0.400 to –0.650). However, for the mixed group of households under the Time-Of-Use tariff, there was a weak negative correlation between socio-demographic diversity and financial risk. This weak correlation ranged from 0.005 to –0.618. For the mixed group with both tariff types, there was a strong negative correlation between customer diversity and financial risk.

Based on the results it is speculated that for the mixed group with both tariff types, the relationship between customer diversity and financial risk depends on the tariff type that dominates the group. That is, if households under the Flat-rate tariff contribute the most to the group's aggregated demand then there will be a strong negative correlation between customer diversity and financial risk. If, however, households under the Time-Of-Use tariff form the major part of the aggregated demand, then the relationship (correlation) between customer diversity and financial risk would be weak. In addition, all the correlation values were found to be statistically significant; that is the probability that these values occurred by chance is less than 0.05.

These results show that tariff type as well as the operational objectives used in residential energy management systems play a significant role not just in reducing risk but also influencing the factors (such as customer diversity) that may affect financial risk.

Finally, this work demonstrated that the retailer does not necessarily need appliance level electricity consumption data to model and analyse the possible portfolio effects of the large-scale deployment of residential energy management systems. Strategically, these results can be used to inform economic feasibility studies and studies to investigate possible effects that large-scale deployment of residential energy management systems can have on the retail portfolio outcomes.

4.5 Discussion

The results obtained in this Chapter bring into focus a few issues surrounding the cost benefit of residential energy management systems. The cost-benefit of residential energy management systems depends on the socio-demographic of the customer, the tariff type and the operational objectives used by the device. This explains why there has been such a discrepancy across previous research findings about the monetary benefit that these systems can provide for the customer. The analysis presented does provide an opportunity to see how the benefit changes according to the customer profile and the device type. This is useful to any retailer wanting to invest in a residential energy management system product. By understanding these specifics, the retailer can dovetail strategies to help customers maximise their benefit from the system and justify the use of specific objectives to operate the device.

From the retailer's perspective, it is important to undertake a cost-benefit analysis before implementing residential energy management systems on a large scale and to evaluate the probable cost and the revenues that might be generated. The analysis presented in this Chapter helps to evaluate the financial feasibility of these devices and can help determine whether possible demand response projects should be pursued or dropped. Furthermore, it is important to keep in mind that the results for both the retailer and the customer are based on forecasted results of the generalised model presented in Chapter 3. The results present a view of what can be expected in the future if these devices are installed on a large scale. Such forecasting capabilities enable the retailer to make strategic decisions on expected profit and risk.

For example, one of the weaknesses of the "Low Carbon" London project is that £28 million had to be spent over a four-year period in order to attain cost benefit results. Having the ability to forecast ahead the cost-benefit outcomes of technologies such as residential energy management systems would reduce the amount of money and time necessary to obtain data useful for strategic decision making. This would reduce the need for such resource-intensive exploratory projects.

Finally, the cost-benefit analysis done for residential energy management systems indicates the importance of comparing customer socio-demographic, tariff and operational objectives for the devices. For other demand response devices (such as electric vehicles) it is important to do a full-factorial analysis like the one done in this Chapter. An understanding of ways to maximise the benefit to the customer and retailer, and how technologies can change well established relationships between factors such as customer diversity and risk can provide valuable insight into smart grid development.

4.6 Concluding remarks

One of the fundamental issues evident in the literature surrounding residential energy management systems is that the cost-benefit of these devices was not clearly understood. In this chapter the generalised residential energy management system model was used to examine how socio-demographic profile, tariff structures, and the choice of operational objectives of these devices, interact to influence their benefits and costs for customers and retailers.

The results indicated that a one-size-fit-all approach to installing residential energy management systems on a large scale is not the most optimal way to maximise benefits for the customer. Different customers require devices that have suitable operational objectives to maximise their benefit. The results also indicated there are some operational objectives that enable the retailer to increase profit whilst others do not. In addition, residential energy management systems can directly influence retail risk by reducing variance in profit for the retailer (as seen in Chapter 3) and can indirectly influence profit by strengthening (or weakening) the relationship between diversity and risk.

Chapter 5

Improving the generalised model: A method for optimally selecting a baseline load profile

5.1 Introduction

A demand response baseline load profile is an estimate of the amount of electricity that a customer would have used were they not participating in demand response [85]. With an established baseline the retailer can measure the amount of demand response provided by a customer by subtracting the customer's reduced demand use from the baseline load profile. The difference between the two profiles would determine how much the customer is compensated for providing demand response. The difference also determines how much the retailer may have saved in terms of cost associated with providing electricity to the household.

Up until this point the generalised model developed in Chapter 3 has followed the traditional approach of measuring demand response using historical data as the demand response baseline in the initial iteration of the generalised model for the residential energy management system (Expression (3.9) Chapter 3). This was done deliberately to ground the development of the model in existing literature. However, it has been indicated by several studies that historical data may not be the most accurate demand response baseline.

Consequently, several other demand response baselines have been developed and used by researchers. These baselines have been fully explored in Chapter 2. Unfortunately, developing different baseline methods has led to the major issue of deciding which baseline is best to measure the demand response of a demand response technology. Any model developed for residential energy management systems should accurately assess the most optimal method for creating a baseline to measure its performance. As such, this Chapter develops an optimisation method for selecting an optimal baseline to measure the demand response of a residential energy management system.

5.2 Characterising cost-benefit for the retailer (b_r)

According to the Modern Portfolio Theory [144] the performance of a retail profit can be expressed in terms of the profit obtained from the portfolio and the variance (or risk) experienced by the portfolio. This can be expressed as a single mean-variance performance metric shown in Equation (5.1).

$$portfolio\ performance\ metric = \frac{\mu_p}{{\sigma^2}_p} \tag{5.1}$$

where	
μ_p	Average revenue earned by the retail portfolio
${\sigma^2}_p$	Variance of profit gained from portfolio

When an asset is added to a portfolio, it can change either the profit or variance in profit received from the portfolio. This causes a change in the portfolio performance metric. This change is considered as the benefit received by the retailer from adding the asset to the portfolio. This benefit (b_r) can be expressed by Equation (5.2).

$$b_r = \frac{\Delta\mu_p}{\Delta{\sigma^2}_p} \tag{5.2}$$

where	
$\Delta\mu_p$	Change in average profit earned by the retail portfolio
$\Delta{\sigma^2}_p$	Change in variance of profit gained from portfolio

Since residential energy management systems can influence average electricity use, then, by extension it can also influence the expected profit that the retailer receives from customers. Moreover, these devices can also influence the variance in electricity use and consequently change the quantity risk experienced by the retailer. Given these observations, it can be expected that if these devices are installed on a large scale, they can influence a retailer's portfolio outcomes; that is, change the retailer's portfolio profit and risk. This was shown in Chapter 4. The general formula for change in portfolio profit ΔP can simply be represented using Equation (5.3).

$$\Delta P = \mu_{p_2} - \mu_{p_1} \tag{5.3}$$

where

μ_{p_2}	Final profit in portfolio after residential energy management systems have been deployed
μ_{p_1}	Initial profit in portfolio before residential energy management systems have been deployed

The effect of these devices on the retail risk requires closer inspection. It was shown in Chapter 4 that residential energy management systems influence the quantity risk faced by the retailer by directly reducing aggregated variance in electricity use and indirectly influencing the effect of customer diversity on risk. This direct and indirect effect needed to be incorporated into the change in risk ($\Delta\sigma^2{}_p$) experienced by the retailer.

The direct effect of the residential energy management system on the variance in revenue received from the customers can be represented by "Cohen's d" [145] given in Equation (5.4). "Cohen's d" metric simply measures the size of the effect that an intervention may have on a variable under investigation [145].

$$Cohen\ d = \frac{\mu_{\sigma_1} - \mu_{\sigma_2}}{\frac{1}{2}(\sigma_1 + \sigma_2)} \tag{5.4}$$

where

μ_{σ_1}	Average variance in profit experienced by the retailer from households before the deployment of residential energy management systems
μ_{σ_2}	Average variance in profit experienced by the retailer from households after the deployment of residential energy management systems
σ_1	standard deviation in profit experienced by the retailer from households before the deployment of residential energy management systems
σ_2	standard deviation in profit experienced by the retailer from households before the deployment of residential energy management systems

In this case "Cohen's d" measures the size of the effect that residential energy management systems have on the variance in electricity use of the retail portfolio after deploying these devices amongst a diverse group of customers.

Similar to "Cohen's d" metric, "Cohen's f^2" metric is used to measure the indirect effect of these devices on retail risk through their influence on customer diversity [146]. According to Cohen's f^2 statistic, if two variables are correlated then the effect that one variable has on another can be written in terms of their correlation as shown in Equation (5.5).

$$f^2 = \frac{\rho^2}{(1-\rho^2)} \tag{5.5}$$

where

f^2	Effect size metric measuring the effect of diversity on variance
ρ^2	Correlation between diversity and variance

The authors of [146] indicated that Cohen's f^2 is simply an extension of Cohen's d. These two values are related to each other as shown in Equation (5.6).

$$d^2 = 2k \times f^2 \tag{5.6}$$

The variable "k" in Equation (5.6) is the number of customer sets sampled to establish the relationship between variance and diversity [147]. By equating Equation (5.4) and Equation (5.5), the change in risk produced by the residential energy management system can be expressed in terms of its direct and indirect effects on risk.

$$\frac{\left(\mu_{\sigma_1} - \mu_{\sigma_2}\right)^2}{\frac{1}{4}(\sigma_1 + \sigma_2)^2} = \frac{2k\rho^2}{(1-\rho^2)} \tag{5.7}$$

Multiplying both sides by $\frac{1}{4}(\sigma_1 + \sigma_2)^2$ gives Equation (5.8).

$$\left(\mu_{\sigma_1} - \mu_{\sigma_2}\right)^2 = \frac{2k\rho^2}{(1-\rho^2)} \times \frac{1}{4}(\sigma_1 + \sigma_2)^2 \tag{5.8}$$

Simplifying and taking the root of both sides gives Equation (5.9).

$$\mu_{\sigma_1} - \mu_{\sigma_2} = \frac{k}{2} \times \frac{\rho(\sigma_1 + \sigma_2)}{\sqrt{(1-\rho^2)}} \tag{5.9}$$

Rewriting Equation (5.9) gives Equation (5.10).

$$\Delta\sigma^2{}_p = \frac{k}{2} \times \frac{\rho(\sigma_1 + \sigma_2)}{\sqrt{(1-\rho^2)}} \tag{5.10}$$

Equation (5.10) expresses the change in financial variance experienced by a portfolio in terms of the influence of these devices directly on retail risk and indirectly on customer diversity. Using Equation (5.3) and (5.10) the retail benefit (Equation (5.2)) can be rewritten as Equation (5.11). Equation (5.11) represents the change in portfolio performance (or benefit) that the retailer can expect with the mass deployment of residential energy management systems.

$$b_r = \frac{2}{k} \times \frac{\Delta P\sqrt{(1-\rho^2)}}{\rho(\sigma_1 + \sigma_2)} \tag{5.11}$$

5.3 Generalised method for optimally selecting a baseline

Several authors model demand response programs by their ability to maximise the social welfare of the stakeholders of the program [110]. Social welfare is defined as the weighted sum of the benefits of the stakeholders of the demand response program [110]. If the focus is restricted to the customer and retailer then according to [110, 148], the weighted sum of their benefits can be expressed by Equation (5.12).

$$U = \beta_1 . b_c + \beta_2 . b_r \tag{5.12}$$

where	
U	Total social welfare from the demand response program
b_c, b_r	Optimal cost-benefit for the customer (b_c) and retailer (b_r)
β_1, β_2	Weights indicating the relative importance of customer and retailer to the program. The weight values are generally arbitrarily selected

In [149] the authors suggested that optimally designing any aspect of a demand response program becomes a matter of maximising the total social welfare (U) derived from the program.

This is generally known as the social welfare maximisation problem [150] and is shown in Expression (5.13).

$$Maximise\ U = [\beta_1 . b_c + \beta_2 . b_r] \tag{5.13}$$

$$\text{Subject to } B_L \leq d_t^{\ *} \leq B_U$$

where	
B_L	Lower limit for demand response from participants of demand response program
$d_t^{\ *}$	Hourly reduced demand from participants of demand response program after demand response event
B_U	Upper limit of demand response from participants of demand response program. This is often used as the baseline to measure demand response from participants.

As with all other aspects of designing a good demand response program, when choosing a baseline method to create a baseline for the residential energy management system, it must be selected to maximise the overall social welfare of the customer and retailer. Therefore, Expression (5.13) is one of the considerations that must be accounted for when selecting a baseline method.

When selecting an appropriate baseline for a demand response program, the accuracy and bias of that baseline must be taken into account; baselines with the highest accuracy and lowest bias are most appropriate [24]. Ensuring the highest accuracy from a baseline involves minimising the error in measuring demand response [151].

There are several methods for measuring baseline error [151]; one method most commonly used is to define the error in terms of the bias and variance produced by the baseline. Baseline bias is the tendency of the baseline to make assumption about the customer demand that is not necessarily true [152]. For example, "*Last Y days*" baseline method assumes that the electricity use of the customer for the current day can be calculated from averaging the last "*Y*" days. This assumption is not necessarily true and can produce bias in estimating demand response. High bias baseline methods tend to produce less accurate baselines.

Additionally, a baseline is said to have high variance when there is a tendency of the baseline to over-fit data. Such baselines accurately predict the data used to create it but perform poorly when used to predict future demand response [152]. For example, a baseline created using the "*Neural Network*" baseline method often tends to overfit data and produce inaccurate results if the parameters for the neural network are not carefully tuned.

Therefore, to reduce errors produced by a baseline, a baseline method must be selected so that both bias and variance is minimised. This is commonly known as the "Bias-Variance trade-off problem" and can be represented by Expression (5.14).

$$Minimise\ RMSE = \sqrt{bias^2 + variance} \tag{5.14}$$

From Expression (5.14), RMSE represents the root mean square error associated with a baseline and is a measure of the accuracy of the baseline. Minimising an equation is equivalent to maximising its reciprocal. As such, Expression (5.14) can also be rewritten as a maximisation problem shown in Expression (5.15).

$$\begin{array}{ll} Maximize & \dfrac{1}{RMSE} \\ Subject\ to & RMSE > 0 \end{array} \tag{5.15}$$

The condition RMSE greater than zero was put in place to ensure that Expression (5.15) had real solutions. It was also put in place to acknowledge that there are no perfect baselines (that is, baselines free from errors). It stands to reason that in the process of selecting a baseline the social welfare of the stakeholders of the baseline and the accuracy of the baseline must be maximised. Therefore, Expression (5.12) and (5.15) can be combined into a single maximisation problem. This is shown in Expression (5.16).

$$Maximize\ \ U\ and\ Maximize \frac{1}{RMSE} \tag{5.16}$$

A more compact form of Expression (5.16) is given in Expression (5.17).

$$Maximize\ E_A = \frac{1}{RMSE} \times (\beta_1 . b_c + \beta_2 . b_r) \tag{5.17}$$

$$Subject\ to \quad l_t \leq d_t^* \leq b_t \quad and \quad RMSE > 0 \qquad for, \forall\ l_t, \forall\ d_t^* and\ \forall\ b_t$$

Where

E_A	Economic advantage of selecting a baseline to measure the demand response of residential energy management systems.
$RMSE$	Root mean square error produced by the baseline. This is a measure of the baseline's accuracy and bias.
b_c, b_r	Benefit derived from the demand response of the residential energy management systems for the customer (b_c) and retailer (b_r)
β_1, β_2	User defined weights that indicate the relative importance of the demand response benefits of the customer and retailer
b_t	Hourly demand from baseline load profile
d_t^*	Reduced hourly demand from household after demand response event
l_t	Hourly base load for household; i.e., load that needs to be serviced continuously within the household (for example refrigerator)

From Expression (5.17), "E_A" represents the number of units of benefit (social welfare) the customer and retailer collectively gain from the demand response program considering the baseline's accuracy. The higher the value of "E_A", the more economically advantageous for both the customer and retailer it is to select the given hourly baseline load profile.

5.4 Characterising weights for the economic model

In the generalised economic model for optimally selecting a baseline $\beta_1$and β_2 can take any arbitrary value. These weights simply indicate the relative importance of the social welfare of the customer and retailer. The weights were set to the following values:

Table 5.1. Suggested weights for cost-benefit values b_c and b_r
$\beta_1 = 1$
$\beta_2 = \frac{k\rho(\sigma_1 + \sigma_2)}{2}$

The first weight (β_1) for the customer cost-benefit (b_c) was trivially given the value of 1.

The weight (β_2) for the retail cost-benefit (b_r) was selected so that it cancelled out the denominator in Equation (5.11) (the equation that defines b_r). Since ρ (the correlation between diversity and quantity risk) can take any value, it is possible that it can be zero. This would make Equation (5.11) undefined. Therefore, to eliminate that possibility, the value of weight (β_2) was set so that the correlation value in the denominator was cancelled out.

In addition, weight (β_2) also included "k" (which is the number of groups made in order to get the correlation between diversity and quantity risk). In this research the value of "k" was 20 sets (page 91). This was an arbitrary value and does not have any impact on the retail cost-benefit (b_r); therefore, it needed to be eliminated from Equation (5.11) as well.

Finally, weight (β_2) also included variables σ_1 and σ_2; these are the variances of the household before and after demand response. Since these values have the possibility of being zero, they have the potential to make Equation (5.11) undefined. Therefore, to eliminate that possibility, the value of weight (β_2) was set so that these values are also cancelled out. Consequently, the weights suggested in Table 5.1 resulted in the following formulation for the weighted cost benefits of the customer and retailer:

$$\beta_1 . b_c = b_c \qquad\qquad \beta_2 . b_r = \Delta P\sqrt{(1-\rho^2)} \tag{5.18}$$

Having characterised the different variables in Expression (5.17), the economic advantage (E_A) of a given baseline could have been measured. The baseline with the highest economic advantage (E_A) is considered the optimal baseline to measure the demand response of the installed residential energy management systems. Nevertheless, in the process of defining a new model, the model complexity, model fit, and model convergence needed to be addressed.

5.5 Characterising model complexity, fit and convergence

Model complexity measures the number of parameters required by the model to accurately capture patterns, processes and relationships between variables in the data [111], while model fit measures how well the model generalises to other similar data [111]. The more parameters a model has, the more it can explain variations in a set of data. However, if a model has too many parameters, this decreases the generalisability of the model (that is, the model's fit). According to [153], model complexity and fit can be measured using a single metric called the Bayesian Information Criterion metric. The formula for the Bayesian Information Criterion metric is given in Equation (5.19).

$$BIC = k \times ln(n) - 2 \times ln(\hat{L}) \tag{5.19}$$

Where	
BIC	Bayesian Information Criterion metric
k	Number of parameters in the model. This is the case of the (E_A) model shown in Expression (5.17), there are 5 parameters.
$\hat{L}$	Likelihood function.
n	Number of data points used to calculate the model.

In the case of the economic model developed in Expression (5.17), the baselines examined would have different model complexities and fit associated with them. The term $k \times ln(n)$ in Equation (5.19) is constant for the economic advantage model presented in Expression (5.17) and does not depend on the baseline type. However, the term $ln(\hat{L})$ depends on the errors produced by the baseline being examined; this term is calculated using the formula presented in Appendix G. The lower the value of the Bayesian Information Criterion (BIC), metric the more suitable a baseline model is for measuring the demand response of the installed residential energy management systems. Examining model complexity and fit is important because it will provide evidence that the baseline that produces the optimal economic advantage (E_A) is also the baseline which best models the demand of the customer.

In addition to model complexity and fit, model convergence was also assessed. Model convergence determines whether the model has a unique maximum solution [154]. If the model has a unique maximum solution (call the global optima) then, any optimisation technique can be used to find this solution. For this research the primary technique used to find the global optima for Equation (5.17) is the particle swam optimisation technique which was chosen because it is excellent at escaping suboptimal solutions, finding optimal solutions and is simple to implement [155]. The technique uses several iterations to find an optimal solution to a given problem. According to [156], the output produced by the optimisation technique after each iteration can be used to characterise the convergence of the model given in Equation (5.17). If the model has a global optimum, then the output would converge to a constant value as the algorithm progresses through its iterations (irrespective of the baseline or type of customer being examined). Once the economic model was fully characterised the baselines to be examined needed to be defined.

5.6 Characterising baselines used to measure demand response

Baseline load profiles are generally named according to the method used to calculate them. Nine of the most used methods were chosen for analysis in this research and a full description of each is provided in Table 2.5, Chapter 2. Each baseline method requires parameters to calculate their baselines [87, 89]. The general parameters used in this research for each baseline described in Table 2.5 are given in Table 5.2. Historical data was included in Table 5.2 as a reference.

Table 5.2. Parameters used for different baseline methods [89]

Baseline Method	Parameterization*	
1. Historical Data		
2. Last Y days	$Y = 10\ days$	
3. Low X of Y days	$X = 4\ days,$	$Y = 10\ days$
4. Mid X of Y days	$X = 4\ days,$	$Y = 10\ days$
5. High X of Y days	$X = 4\ days,$	$Y = 10\ days$
6. Exponential Moving Average	$\alpha = 0.9,$	$Y = 10\ days$
7. Linear Regression	$X = 5\ days$	
8. Polynomial Interpolation	$X = 5\ days$	
9. Neural Network	$X = 5\ days$	

* the definitions given in Table 2.5, Chapter 2, explains how these parameters are used to create the different baseline load profiles

For each of the two groups of households (customers paying Flat-rate and Time-Of-Use tariff), the methods listed in Table 5.2 coupled with the smart meter data obtained from the "Low Carbon" London project were used to create 9 different baselines for a typical day. To illustrate the baselines that were produced, a comparison of the load profile of a typical day for customers on a Flat-rate tariff with the baselines created is given in Appendix F.

5.7 Simulating the economic advantage E_A of the selected baselines

Having characterised the different variables used in the economic model given in Expression (5.17) and establishing metrics to measure model complexity, fit, and convergence, simulating the baselines and optimally selecting the correct baseline for each customer group was done. To carry this out, the average monthly load profile for the first subgroup of households (households paying a Flat-rate tariff) was found and used to represent the electricity use of a typical customer within that subgroup. Using the average monthly load profile, the first baseline method from Table 5.2, "Historical Data", was selected to create a baseline monthly load profile. The baseline load profile was coupled with the residential energy management system model given in Chapter 3 to simulate and calculate the optimal demand response of the device for different combinations of that device's objectives. The baseline load profile was the “d_t” from which the reduction in average and peak-to-average demand was calculated. The method used to calculate “E_A” for each baseline is presented in Figure 5.1.

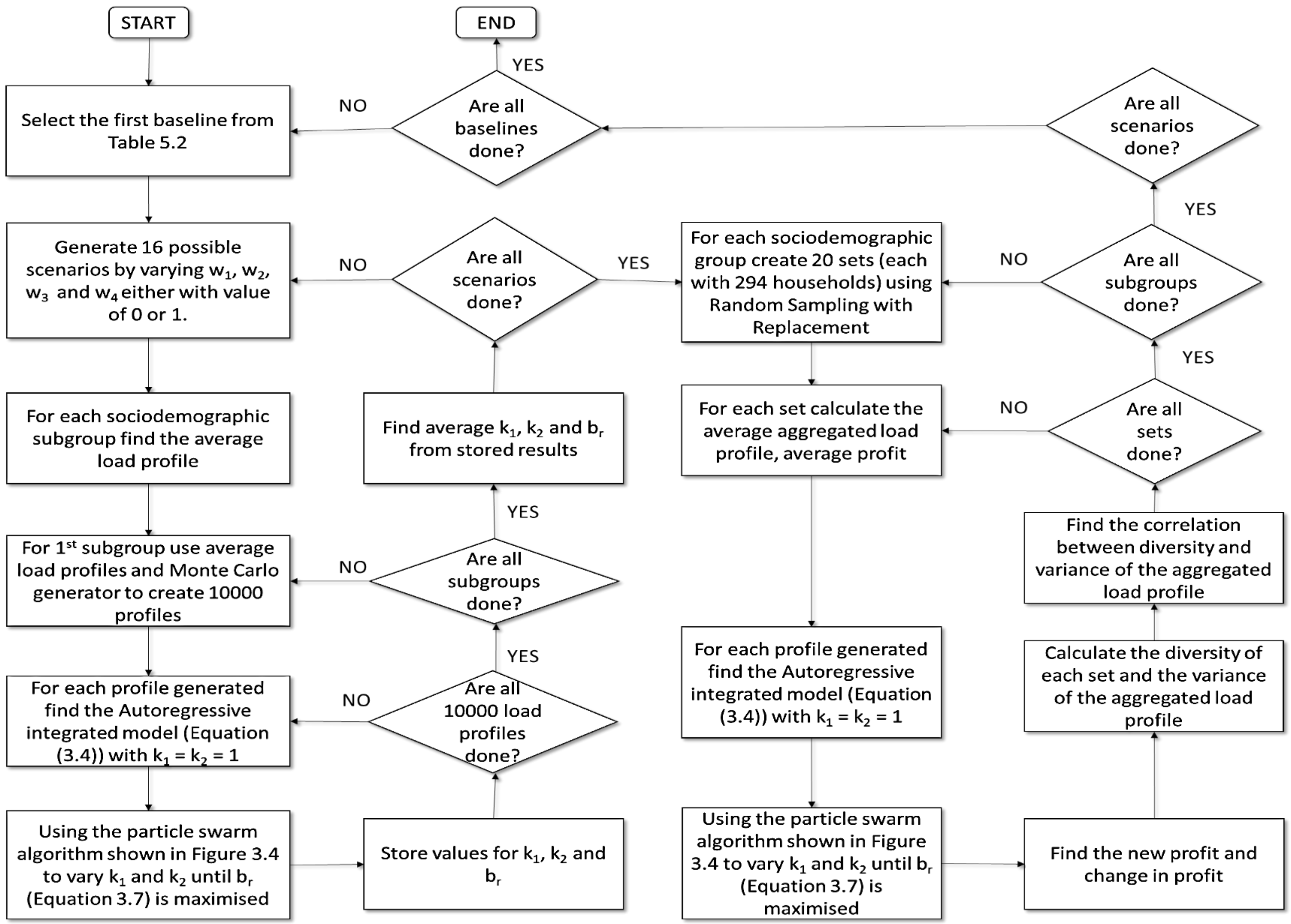


Figure 5.1. Flow chart for procedure used to calculate E_A for each baseline

In accordance with the procedure, the first baseline “Historical Data” was selected from Table 5.2. This baseline will be used as the original customer demand “d_t” from which the customer benefits and cost objectives (given in Table 3.1) will be calculated.

Each scenario was examined for the first subgroup of customers using the algorithm given in Figure 3.3. In accordance with the algorithm and using the average monthly load profile created for the first subgroup, the Monte Carlo generator (Equation (3.10)), was used to generate 10,000 monthly electricity use profiles.

The 10,000 load profiles were each compared to the “Historical Data” baseline for the same period and the root-mean-square error value for each generated profile was found. This resulted in 10,000 root-mean-square error values which were used to find an average root-mean-square error value. This average represented the root-mean-square error for the group if they used “Historical Data” baseline. The variance of the root-mean-square errors ($\sigma_{\varepsilon}{}^{2}$) was also found and used to compute the Bayesian Information Criterion value for the “Historical Data” baseline. To compute the Bayesian Information Criterion value using Equation (5.19), the variables “k” was set to 5 and “n” was set to 720 (there are 720 hours in a 30-day month). This value represented the “Historical Data” baseline’s complexity and fit.

For the first scenario shown in Table 3.6, the 10,000 load profiles generated were fed into the residential energy management system model to find 10,000 values for the optimal cost-benefit ratio for the customer (b_c) and 10,000 optimal load profiles for the subgroup. The 10,000 results for cost-benefit ratio (b_c) were used to find an average cost-benefit for a typical customer for the first subgroup. This was repeated for the other 15 scenarios shown in Table of Appendix E.

This resulted in 16 average values for cost-benefit ratio (b_c) for the first subgroup (one for each scenario shown in Table of Appendix E). These 16 values were used to calculated 16 values for the weighted customer cost-benefit ($\beta_1 . \mathrm{b_c}$) using Equation (5.18).

Having determined weighted customer cost-benefit ($\beta_1 . b_c$) for the "Historical Data" baseline for each scenario shown in Table of Appendix E, it was necessary to determine the weighted retail cost-benefit ($\beta_2 . b_r$). Using the 10,000 optimal load profiles for the first subgroup of customers (for each scenario shown in Table of Appendix E), the percentage change in aggregated profit (ΔP) for the retailer was calculated using the algorithm shown in Table 4.1. This resulted in 16 average values for change in aggregated profit (ΔP) for the first group of customers (one for each scenario shown in Table of Appendix E).

After change in profit (ΔP) was dealt with, the correlation (ρ) between customer diversity and retail risk was determined for the first subgroup. To do this, 20 sets of households were created. Each set comprised 291 households chosen from the subgroup using a "Random Sampling with Replacement" [157] technique. The number of sets created was determined arbitrarily. However, the size of each set was determined using a statistical table from ref. [141]. According to the statistical table [141], to determine the correlation between customer diversity and risk at a 95% confidence level and with a 5% margin of error, each set must have at least 291 households. The confidence level specifies how certain the correlation results are expected to be [141].

The diversity of each of the 20 sets was calculated using Equation (4.1). The average aggregated month load profile for each of the set was also found. For each scenario of operational objectives shown in Table of Appendix E, the sets' average monthly load profiles were fed into the residential energy management system model and the optimal load profiles was obtained. This resulted in 20 optimal load profiles for each scenario shown in Table of Appendix E. The risk (variance in profit) from these optimal load profiles were calculated and recorded. Using the results, the correlation (ρ) between the diversity and retail risk for each scenario was found. This resulted in 16 correlation values (one for each scenario shown in Table of Appendix E).

Having found change in profit (ΔP) and correlation (ρ) for each scenario of operational objectives shown in Table of Appendix E for the first subgroup, the weighted optimal cost-benefit for the retailer ($\beta_2.b_r$) for each scenario was determined.

Once this was done, the weighted benefit-cost ratio for the customer ($\beta_1.b_c$), the retailer ($\beta_1.b_r$) for each scenario and the average root-mean-square-error value for the "Historical Data" baseline was used to calculate the economic advantage "E_A" of the "Historical Data" baseline under each scenario for the first subgroup. This resulted in 16 values of the economic advantage "E_A" of the "Historical Data" baseline for the first subgroup.

The process of calculating 16 values of the economic advantage "E_A" of the "Historical Data" baseline for the first subgroup of customers for each scenario was repeated for the 17 customer groups that pay a Flat-rate tariff only. The average "E_A" for the 18 customer groups that paid a Flat-rate tariff was found for each of the 16 scenarios. This resulted in 16 average "E_A" values for customers paying a Flat-rate using "Historical Data" as a demand response baseline. In the same manner 16 average "E_A" values were found for each of the other 8 baselines shown in Table 5.2 for customers paying a Flat-rate tariff and then for customers paying a Time-Of-Use tariff.

Finally, the value of the economic advantage of the baselines depends on the optimal load profiles obtained by the particle swarm algorithm. To show model convergence, the typical load profile created for the first customer group ("Lavish Lifestyle" customers) was coupled with the residential energy management system model, and an optimal load profile was found using the algorithm shown in Figure 3.3 for each scenario in Table of Appendix E.

The load modifying algorithm (Figure 3.3) consists of two parts, the load shifting algorithm and the load reduction algorithm based on the particle swarm optimisation. Convergence for the load shifting algorithm is assured since there are only a finite number of ways to shifting electricity use to satisfy the condition that the retailer must make an increase in profit (see Table 2.7 in Chapter 2). However, whilst it has been shown that the load reduction algorithm has a global maximum (Expression (3.8), Chapter 3), convergence for the load reduction particle swarm optimisation algorithm still needs to be checked. The particle swarm optimisation algorithm was run for 150 iterations and after each iteration, the global optima was recorded. This was done for each scenario shown in Table 3.6. The global optimal solutions were plotted against the iterations. This was repeated for the Time-Of-Use subgroup of customers. The graphs produced were checked for convergence; that is, if the graphs settled on a constant value within the 150 iterations.

5.8 Simulation results

The optimal economic advantage “E_A” calculated for each subgroup of customers and for each of the 16 scenarios was presented in Table 5.3 and Table 5.4. Every entry in these tables shows the economic advantage of selecting a baseline method for a given operating scenario of the residential energy management system. In Table 5.3, for example, when selecting a “High X of Y days” method for creating a baseline for Flat-rate customers in “scenario 8” (where the device is operated to produce electricity bill, emissions and tax savings for the customer and an increase retail profit), the optimal economic advantage “E_A” was found to be “2.335”. This means that the customer and retailer would make a total of “2.335” units of benefit for every unit of cost they experience from the “High X of Y days” baseline.

It is clear from Table 5.3 and Table 5.4 that the economic advantage of the baseline methods is influenced by the operating behaviour of the residential energy management system and the tariff paid by the customer. An inspection of the last column in Table 5.3 shows that creating a baseline using the “Mid X of Y” method provides the highest average economic advantage (–0.766) for both the customer (paying a Flat-rate tariff) and the retailer irrespective of the operating objectives of the residential energy management system. However, it is also noted when examining the last row of Table 5.3 that the economic advantage when a single baseline is used for all customers is low, ranging from (–16.090 to 0.959). This result suggests that using a single baseline to measure the demand response performance of all customers may not be appropriate; that is, the a one-size-fits-all approach that is traditionally used for demand response programs may not be the most optimal approach to measuring demand response for residential energy management systems. A better approach would be to allow the retailer to communicate with the device to select a customised baseline for a customer or customer group that maximises the economic advantage "E_A" of its demand response. The device can then report to the retailer the forecasted demand and demand response expected for the household. In effect the device would ensure that, locally, the customer's welfare is maximised and globally, the retailer's welfare is also maximised.

Every column in Table 5.3 shows that as the operating conditions of the residential energy management system changes, the baseline method that gives the highest economic advantage to the customer and retailer also changes. For example, for "scenario 7" the optimal baseline method is the "Linear Regression" method which will give a total economic advantage "E_A" of "5.230" units of benefit for Flat-rate customers. But for "scenario 8", for the same set of customers, the optimal baseline method is the "High X of Y" method which will give a total economic advantage "E_A" of "2.335" units. This implies that when selecting a baseline method to measure the performance of a demand response program involving residential energy management systems the operational objectives of the systems, should be considered.

The same analysis was done on Table 5.4 which shows the economic advantage of the selected baseline methods for customers paying a Time-Of-Use tariff and for the retailer. The last column of Table 5.4 shows that the baseline method with the highest economic advantage irrespective of the operating scenario of the residential energy management system is "Neural Network" method whose "E_A" is –0.253 units, a loss of benefit. This reinforces the idea that in the process of installing residential energy management systems, the customer and retailer must be very specific about the operational objectives used to run the device (when considering the baseline used to measure its performance). Like Table 5.3, every column in Table 5.4 shows that as the operational conditions of the residential energy management systems changes, the baseline method that gives the highest economic advantage to the customer and retailer also changes; ranging from –16.337 units to 2.215 units (a slightly larger ranger than for Flat-rate customers). This result supports the idea that a single baseline to measure the demand response performance of all customers may not be appropriate.

Table 5.3. Economic Advantage E_A of selected baseline methods for customers paying a Flat-rate tariff

Baseline Methods	Scenarios																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	**Mean**
Historical Data	0.000	-11.360	-14.927	-18.487	-1.919	3.738	1.562	0.894	-0.026	-0.027	-0.028	-0.028	-0.029	-0.028	-0.029	-0.026	-2.545
Last Y days	0.000	-6.833	-4.533	-36.233	-3.515	0.262	0.990	0.827	-0.029	-0.028	-0.025	-0.026	-0.030	-0.029	-0.029	-0.028	-3.079
Low X of Y days	0.000	-12.030	-19.940	10.279	-15.990	1.675	1.275	0.293	-0.023	-0.025	-0.022	-0.024	-0.024	-0.024	-0.026	-0.023	-2.164
Mid X of Y days	0.000	-10.896	-16.035	1.353	6.497	1.686	4.518	0.824	-0.024	-0.026	-0.025	-0.027	-0.027	-0.025	-0.024	-0.025	-0.766
High X of Y days	0.000	-10.606	-43.909	-14.895	0.491	0.979	0.555	2.335	-0.023	-0.022	-0.020	-0.022	-0.022	-0.019	-0.023	-0.019	-4.076
Exponential Moving Average	0.000	-18.622	-19.234	-1.010	2.675	-5.421	1.834	-0.447	-0.033	-0.034	-0.029	-0.031	-0.032	-0.032	-0.030	-0.033	-2.530
Linear Regression	0.000	-10.376	-13.628	0.905	-0.791	1.703	5.230	0.190	-0.025	-0.027	-0.024	-0.024	-0.026	-0.025	-0.028	-0.024	-1.061
Polynomial Interpolation	0.000	-11.644	-15.803	0.523	-1.884	1.034	1.248	-1.923	-0.023	-0.025	-0.023	-0.024	-0.024	-0.024	-0.022	-0.023	-1.790
Neural Network	0.000	-10.708	3.201	-0.465	0.001	2.974	-14.687	1.068	-0.025	-0.024	-0.023	-0.024	-0.026	-0.026	-0.025	-0.025	-1.176
Mean	0.000	-11.453	-16.090	-6.448	-1.604	0.959	0.280	0.451	-0.026	-0.027	-0.024	-0.025	-0.027	-0.026	-0.026	-0.025	-2.132
Variance	0.000	9.482	163.976	201.514	37.794	6.822	34.130	1.368	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	28.443

Table 5.4. Economic Advantage E_A of selected baseline methods for customers paying a Time-Of-Use tariff

Baseline Methods	Scenarios																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	**Mean**
Historical Data	0.000	-7.125	-8.346	4.305	1.723	-0.080	0.609	0.334	0.013	0.013	0.012	0.014	0.014	0.013	0.013	0.014	-0.530
Last Y days	0.000	-6.107	-7.106	-7.629	1.854	1.968	1.134	0.413	0.013	0.012	0.012	0.012	0.011	0.012	0.012	0.015	-0.961
Low X of Y days	0.000	-5.853	-5.553	-0.154	-0.653	0.764	0.929	0.284	0.011	0.010	0.009	0.011	0.011	0.010	0.011	0.012	-0.634
Mid X of Y days	0.000	-11.657	-4.254	-3.457	2.071	-2.505	1.157	0.593	0.013	0.012	0.010	0.011	0.012	0.012	0.012	0.014	-1.122
High X of Y days	0.000	-6.770	-1.940	-27.721	2.773	1.092	-0.663	0.395	0.011	0.010	0.009	0.010	0.011	0.009	0.009	0.012	-2.047
Exponential Moving Average	0.000	-12.713	-9.233	-6.618	3.033	1.805	1.726	0.517	0.017	0.016	0.016	0.020	0.019	0.020	0.015	0.021	-1.334
Linear Regression	0.000	-6.248	-4.251	4.825	1.084	-3.497	-0.829	0.477	0.014	0.011	0.012	0.013	0.014	0.014	0.012	0.016	-0.521
Polynomial Interpolation	0.000	-5.431	-102.900	97.260	2.559	0.983	0.908	0.417	0.013	0.013	0.013	0.012	0.013	0.013	0.011	0.014	-0.381
Neural Network	0.000	-7.964	-3.454	-3.070	5.492	3.760	0.374	0.724	0.010	0.010	0.009	0.011	0.010	0.010	0.009	0.014	-0.253
Mean	0.000	-7.763	-16.337	6.416	2.215	0.477	0.594	0.462	0.013	0.012	0.011	0.013	0.013	0.013	0.012	0.015	-0.865
Variance	0.000	6.903	1059.290	1252.840	2.717	5.060	0.719	0.018	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	145.472

Overall, the economic advantage associated with the baseline, irrespective of customer type and operational objective was higher for Time-Of-Use customers (overall average "E_A" of –0.865 units) than for Flat-rate customers ("E_A" of –2.132 units).

This result agrees with the well-known notion that Time-Of-Use tariff is generally better for customers than the Flat-rate tariff. However, what is interesting to note is that the variance in economic advantage for Flat-rate customers (28.443 units^2) is less then with Time-Of-Use customers (145.472 units^2). This implies greater stability of benefits for Flat-rate customers.

Finally, it is noteworthy to mention that the generalised economic model presented in Expression (5.17), only considers the economic advantage of the customer and retailer using a particular baseline method. The model can be extended to include other stakeholders like the distribution system operator.

Furthermore, using the economic model provided in this research can help to identify not just the optimal baseline, but also the operating conditions of the technology that would produce the highest cost-benefit for all stakeholders involved.

To support the observations made in Table 5.3 and Table 5.4, the Bayesian Information Criterion values was calculated for the different baselines. The result is shown in Figure 5.2.

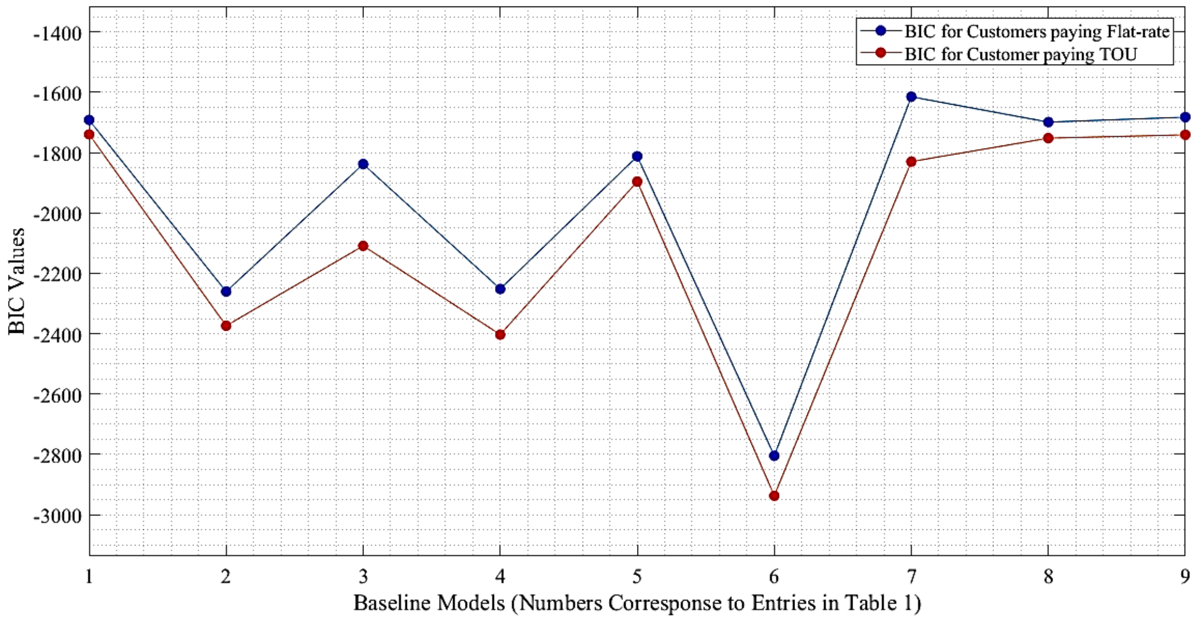


Figure 5.2. Bayesian Information Criterion (BIC) values for different baselines

Lower BIC values indicate better model fit and model complexity. Therefore, it was clear that "*Exponential Moving Average*" baseline had a better model fit and complexity to measure the demand response of customers paying a Flat-rate and Time-Of-Use tariff. This result shows that even though "*Mid X of Y days*" had a highest economic advantage for the Flat-rate customers (as seen in Table 5.3), it may not be the best fitting model for measuring demand response. This result signifies that it is left to demand response program participants to decide which is more important, economic advantage or model complexity and fit. Best fitting models would generally have fewer errors associated with them.

Finally, it was necessary to show that as the particle swarm optimisation algorithm progresses through its iterations, the solutions for the optimal load profile from which the economic advantage of a given baseline is calculated converge to a steady value. This involved examining every baseline, customer group and scenario and graphing the solutions of the particle swarm optimisation for every iteration against the number of iterations. For brevity only two graphs are shown in this thesis. These are shown in Figure 5.3 and Figure 5.4. These graphs show the solutions developed by the particle swarm algorithm for "scenario 4" (Table 5.3) for a typical customers paying a Flat-rate tariff (Figure 5.3) and a typical customer paying a Time-Of-Use tariff (Figure 5.4) when measuring the demand response using the "*Historical data*" baseline. These graphs clearly show that as the optimisation algorithm progresses through its iterations, the solutions for the optimal load profile from which the economic advantage of a given baseline is calculated converge to a steady value for both the Flat-rate tariff and Time-Of-Use tariff. All other graphs examining convergence had similar outcomes. This confirms the integrity of the process to calculate the economic advantage E_A.

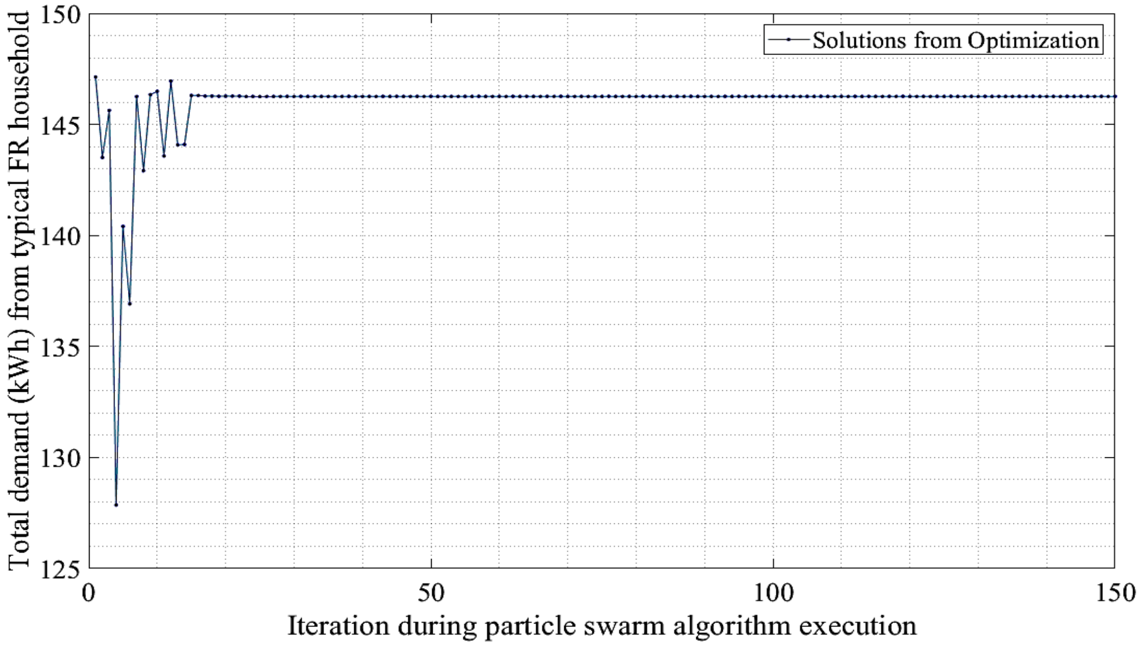


Figure 5.3. Convergence of particle swarm algorithm for Flat-rate customer

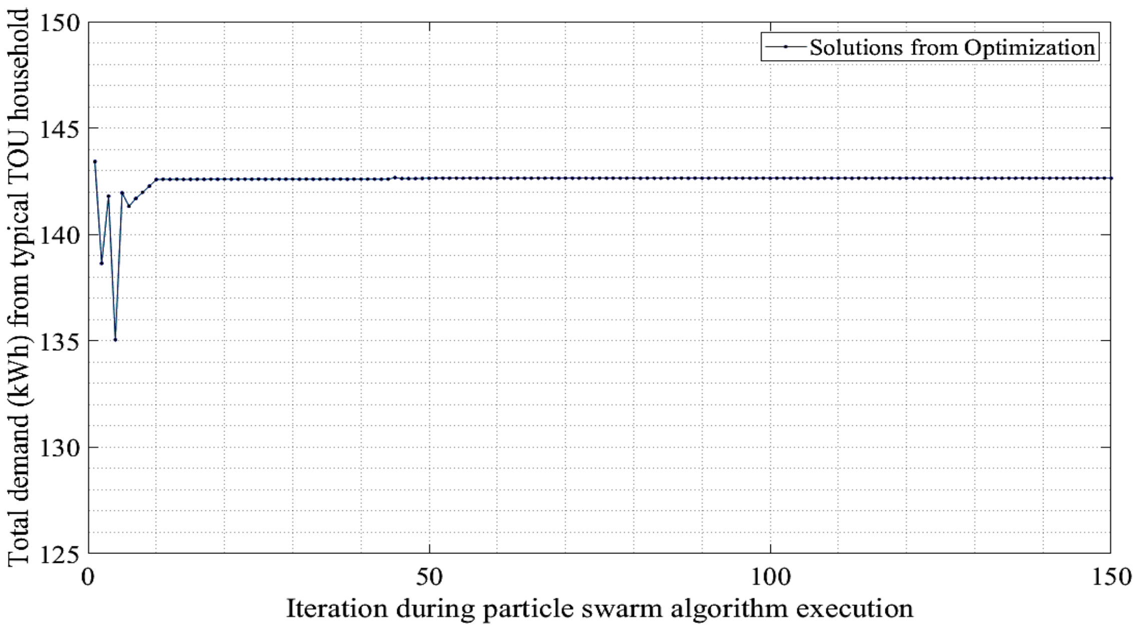


Figure 5.4. Convergence of particle swarm algorithm for Time-Of-Use customer

5.9 Discussion

Traditionally, the administrator of a demand response program (retailer, aggregator or system operator) selects a baseline and then measures the demand reduction (or demand shift) from that baseline to determine the demand response of the group of customers. However, the results shown in Table 5.3 and Table 5.4 show that this may not be the best approach. For example, in the last column of both tables show that the overall economic advantage for any baseline selected is negative. This implies that if a one-size-fit-all approach is taken in selecting a baseline, then in the most optimal scenario of the residential energy management systems, the overall demand response program will make a loss.

Consequently, a different approach needs to be taken to measure demand response programs involving these devices (and possible other smart technologies). Table to Table in Appendix H gives more comprehensive results for the economic advantage "E_A" of each customer group for each tariff type and each scenario of the operational objectives shown in Table 3.6. Examining Table to Table in Appendix H, it is clear that for a given customer situation, there is an optimal "E_A" (and an optimal baseline method) where the retailer and customer can positively gain from the installation of residential energy management systems. These results suggest that the retailer needs to work with each residential energy management system to customise the baseline used to measure the customer's demand response. In doing so, each device can ensure that both the customer and retailer can optimally benefit from the program. Once the optimal baseline is determined by the retailer, the device can communicate to the retailer three key pieces of information; the forecasted electricity use of the household after a demand response event, the forecasted electricity saved during the demand response event and the errors associated with the forecast (autoregressive integrated moving average model in Equation (3.4) by its design is capable of giving errors associated with its forecast).

The "Low Carbon" London Project identified demand response as being a key concept in reducing network investment costs and increasing benefit for customers and retailers. However, the sponsor of the project admitted that there had been little experience with demand response before the project. Retailers who are in similar situations when initially engaging in demand response implementation need to understand the importance of having optimal customisable baselines for obtaining the best economic results.

For example, using the information from Table to Table in Appendix H, it is a simple matter for the retailer to determine the optimal baseline for each customer group that provides the highest economic advantage "E_A" for the customer group. Following this logic, the optimal cost-benefit for the customer and retailer, the root-mean-square value for the baseline and the operational objective for the residential energy management systems that produced this economic advantage can be determined. The results from following this simple procedure are given in Table 5.5 and Table 5.6.

Table 5.5. Optimal conditions to maximise economic advantage for difference customer groups paying Flat-rate tariff

Customer Group	Baseline	Scenario for device	Economic Advantage E_A	Optimal b_c for customer	Optimal b_r for retailer
Lavish Lifestyles	Polynomial Interpolation	4	188.950	6.84	6.84
City Sophisticates	Historical Data	4	5.768	0.48	0.48
Mature Money	Mid X of Y days	4	30.258	1.50	1.50
Starting out	Neural Network	3	175.400	7.31	7.31
Executive Wealth	Exponential Moving Average	4	67.031	1.34	1.34
Not Private Households	Last Y days	5	50.075	0.97	0.97
Steady Neighbourhoods	Linear Regression	5	7.170	0.23	0.23
Career Climbers	Mid X of Y days	4	204.990	7.25	7.25
Successful Suburbs	High X of Y days	4	91.659	1.70	1.70
Modest Means	Low X of Y days	4	301.860	8.75	8.75
Student life	Last Y days	4	120.660	3.39	3.39
Striving Families	Historical Data	6	3.245	0.12	0.12
Comfortable Seniors	Neural Network	5	11.346	0.23	0.23
Countryside Communities	Neural Network	4	61.971	1.90	1.90
Poorer Pensioners	Historical Data	6	16.125	0.28	0.28
Young Hardship	Linear Regression	6	3.657	0.13	0.13
Difficult Circumstances	Exponential Moving Average	5	18.613	0.14	0.14
Struggling Estates	Exponential Moving Average	6	21.919	0.41	0.41
Average			76.705	2.39	2.39

Table 5.6. Optimal conditions to maximie economic advantage for difference customer groups paying Time-Of-Use tariff

Customer Group	Baseline	Scenario for device	Economic Advantage E_A	Optimal b_c for customer	Optimal b_r for retailer
Lavish Lifestyles	Low X of Y days	4	17.140	1.57	1.57
City Sophisticates	Last Y days	5	2.064	0.17	0.17
Mature Money	Mid X of Y days	3	75.268	2.36	2.36
Starting out	Last Y days	5	3.712	0.14	0.14
Executive Wealth	Last Y days	7	9.814	0.26	0.26
Not Private Households	Linear Regression	4	85.783	1.33	1.33
Steady Neighbourhoods	High X of Y days	4	84.586	2.80	2.80
Career Climbers	Historical Data	4	118.940	2.53	2.53
Successful Suburbs	High X of Y days	6	22.215	0.82	0.82
Modest Means	Mid X of Y days	5	16.595	0.68	0.68
Student life	Neural Network	4	18.587	0.45	0.45
Striving Families	Low X of Y days	4	73.263	2.35	2.35
Comfortable Seniors	Exponential Moving Average	4	25.798	0.73	0.73
Countryside Communities	Mid X of Y days	4	12.997	0.32	0.32
Poorer Pensioners	Neural Network	6	42.798	1.08	1.08
Young Hardship	Polynomial Interpolation	4	1967.900	13.60	13.60
Difficult Circumstances	High X of Y days	7	11.687	0.12	0.12
Struggling Estates	Neural Network	5	15.980	0.62	0.62
Average			152.235	1.77	1.77

Once the retailer communicates the baseline and scenario for device (operational objectives of device) and the information shown in Table 5.5 and Table 5.6 to each customer group, demand response can be appropriately measured to maximise the economic advantage for all stakeholders involved. For example it is noteworthy that the average economic advantage from Table 5.5 for customers paying a Flat-rate and the retailer is 76.705 units which is far greater than the economic advantage of using a single baseline (0.959 units) shown in Table 5.3. The same holds true for Time-Of-Use customers who when using customisable baselines, have an average economic advantage of 152.235 units (Table 5.6); however, when using a single baseline, the economic advantage to the Time-Of-Use customers and the retailer is only 6.416 units.

These results suggest that the approach of using optimally selected customisable baselines to measure the demand response from a group of households will ensure the highest benefit from residential energy management systems for all stakeholders. In light of the importance of this approach, the initial model of the residential energy management system presented in Figure 3.2 in Chapter 3 can be augmented with a baseline selection component. This new iteration of the model is shown in Figure 5.5.

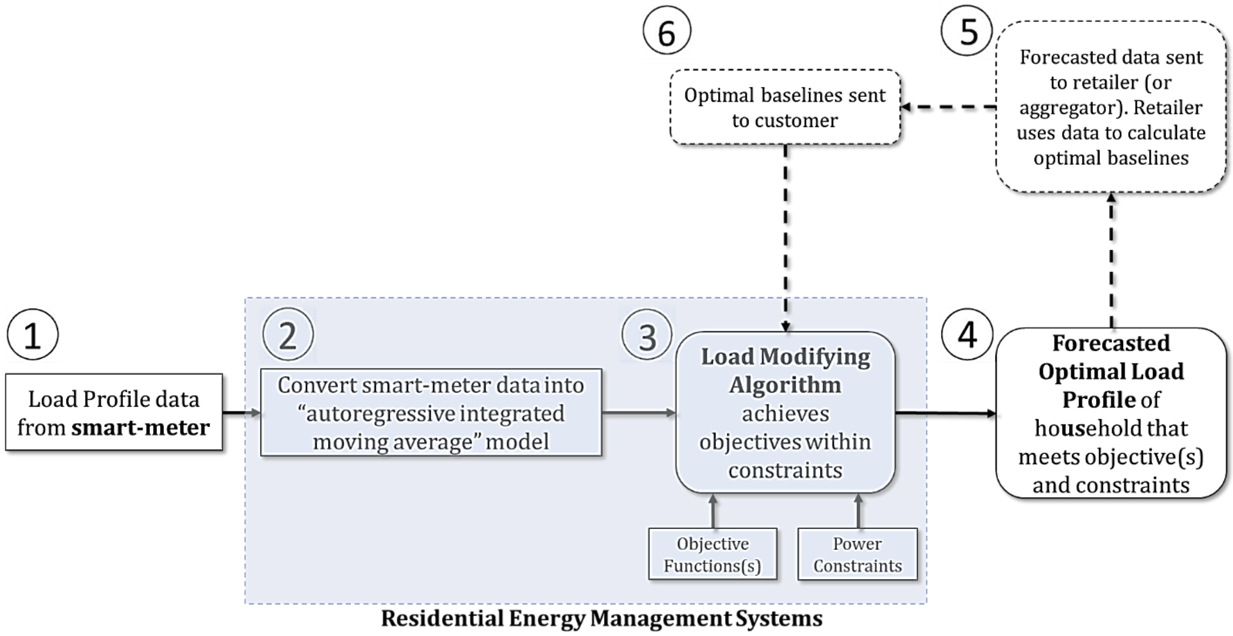


Figure 5.5. Updated model Characterising residential energy management system

The optimal Baseline selection component will use the method described in this chapter to determine the optimal baseline that the residential energy management systems should use in order to ensure the optimal benefit for the customer and the retailer, considering the baselines accuracy and bias. This is a significant contribution to the state-of-the-art as the model will go beyond the traditional method of using historical data to find the demand response of demand response technologies.

The only major issue with this approach is that the system must be designed with security and privacy protocols so that neither the customer nor an external party can tamper with the optimal baseline process of the information (electricity consumption after demand response and amount of demand response) sent to the retailer.

5.10 Concluding remarks

The traditional approach of measuring demand response using historical data as the demand response baseline is not necessarily the most accurate approach to measuring the demand response of residential energy management systems. Consequently, any model developed for residential energy management systems must be able to accurately assess the most optimal method for creating a baseline to measure its performance. As such, this chapter developed a baseline selection method for optimally selecting the most appropriate baseline for measure the demand response of a residential energy management system.

An optimisation method is developed based on maximising the social welfare of both the customer and stakeholder and maximising the accuracy of the baseline. The results showed that the baseline selected depends on the customer socio-demographic, the operational objectives used in residential energy management systems, the tariff paid by the customer, the change in profit made by the retailer and the correlation between customer diversity and quantity risk. It was found the traditional one-size-fit-all approach used to measure electricity demand response is not efficient in maximising the economic advantage received from demand response programs for the customer and retailer. As such it was suggested that each residential energy management system choose its own demand response baseline.

In light of this proposed approach, the generalised model presented in Chapter 3 was then augmented with optimal baseline selection component whose operation was characterised by the optimisation method presented in this chapter. The only weakness identified is that security and privacy need to be ensured when transferring electricity use data from the customer to the retailer.

Chapter 6

Conclusion and Recommendations

6.1 Conclusion

Residential energy management systems are important because they are demand response devices that can be used in both incentive-based and price-based demand response programs. These devices help involve residential customers in contributing to grid development, energy efficiency and environmental sustainability. However, current modelling techniques used for these devices are based on disaggregated data and do not permit realistic large-scale modelling and assessment of their economic feasibility. There is not enough disaggregated data available for large scale modelling; and very little consideration is given to the baseline used to measure the performance of these devices.

The inability to model their large-scale economic feasibility has limited the deployment and potential benefits that can be derived from these devices. As such there was a need to reassess the modelling techniques and develop a method for optimally selecting a baseline to measure their demand response.

Consequently, the central problem addressed in this thesis was to develop a generalised model of a residential energy management system that uses household aggregated load profile data and that optimally selects a baseline to model the behaviour of these devices. In the process of addressing the central problem, six major contributions were made by this thesis. These were outlined in Section 1.4 of Chapter 1 and are summarised as follows:

- A validated generalised model for a residential energy management system was developed using a time series model called an “Autoregressive Integrated Moving

Average" model.

- The generalised model was used to show that the demand response which is provided by these devices is jointly affected by the customer socio-demographic profile, tariff type and the operational objectives used to operate the device.
- Based on a cost-benefit analysis, it was discovered that residential energy management systems can both increase and decrease the profit made by an electricity retailer depending on the set of objectives used to operate these devices.
- Furthermore, these devices have both a direct impact on the risk experienced by a retailer (by reducing the variance in electricity use from households) and an indirect impact by influencing the relationship between customer diversity and retail risk.
- Using the concepts of social welfare maximisation, baseline accuracy-bias trade-off, and the cost benefit analysis done on these devices, a general economic model was created to optimally select a baseline of measuring the demand response of residential energy management systems.
- Using the economic model, it was shown that using a single baseline to measure the demand response of all customers would lead to a loss of social and economic welfare for both the customer and retailer. Instead it was demonstrated that using customised baselines for different customer groups ensured both local maximisation of benefits for the customer and a global, maximization of benefits for the retailer.

6.2 Recommendations for Future Research

The major contributions from this research not only added to the current state of the art but also provided direction for future research that can be explored and further enhance the state-of-the-art. As such the following recommendations are made.

6.2.1 Modelling recommendations

The final generalised model for residential energy management systems presented in Chapter 5 uses an autoregressive integrated moving average model to forecast the demand response of the household whilst finding the optimal reductions in both average and peak-to-average electricity use. However, that model, although sufficiently comprehensive, can be enhanced. There are three recommendations that can be made in this regard.

On reflection, a different regression equation can be used in the model. The autoregressive integrated moving average equation has the limitation of using the previous days' data to predict the current day's electricity use. However, previous literature has shown that other factors such as weather conditions and psychological factors influence the electricity use within the home. Therefore, the fact that a better regression equation can be created to replace the autoregressive integrated moving average model without adversely affecting the methodology laid out in this thesis is one of the strengths of the model presented in this thesis.

Secondly, the objectives used in the objective function for the model can be changed. There were only six major objectives used in this research. Of the six, only four could vary resulting in the 16 possible scenarios examined in this research. However, a different set of objective functions can be used in future analyses. The same approach used in this research, where variable weights are attached to the objectives, could be used for this new set of objectives.

Finally, the model focused on demand reduction and demand shifting. However, infrastructural limitations need to be added to the model to account for the possible effects that peak shifting on a large scale can have on the grid. Residential energy management systems model specific to certain electrical systems can be created. This would limit the generalisability of the model but would permit more comprehensive infrastructural research to be done.

6.2.2 Cost-Benefit analysis recommendations

With regards to the cost-benefit analysis done in Chapter 4, there were important observations that provide guidance for future research. The thesis focused on the cost-benefit of the residential energy management system for both the customer and retailer. However, these are not the only primary stakeholders of demand response programs. The distribution system operator, the national grid operator and other regulatory bodies also have a stake in the mass implementation of residential energy management. Therefore, without significant change in method, the research can be extended to include these stakeholders. It has been suggested that a system dynamic modelling approach be used when considering the interaction of cost and benefits for multiple stakeholders [69]. This can be incorporated into the methodology outlined in this research to ascertain how the cost and benefits of these systems affect the benefit for higher level market participants such as system operators.

In this thesis, specific definitions of cost and benefit for the customer and retailer were used to assess the economic impact of these systems. For example, the cost to the customer was defined as the discomfort and the installation cost of the device. Likewise, the cost to the retailer was defined in terms of risk and the influences of diversity on risk. The cost and benefit definitions can change depending on the specific application of the model. For example, the maintenance costs, depreciation costs of the devices, the added cost of upgrading appliances, the possible attrition or attraction of customers might also be considered in the cost-benefit analysis for the retailer as these factors may influence the revenue and portfolio risk that the retailer may face. This attrition or attraction of customers can be linked to the benefits that the customers derive from the systems.

6.2.3 Model constraints recommendations

Chapter 4 of this research stressed the importance of optimally selecting a baseline from which to measure the model's performance. However, a demand response baseline only deals with the upper constraint of the generalised model presented in Chapter 3. The lower constraint was assumed to be the baseload for the household. However, the lower constraint can be defined in a more comprehensive manner. The lower constraint of the model indicates that the customer is willing to reduce load to the base load of the household. However, the customer may not reduce load to the point that only the basic needs of the household is satisfied; the customer may have other needs or may behave irrationally. More research needs to be done to specifically address the optimal lower demand response limit of the generalised model.

The economic advantage metric created in this thesis is also based on the cost-benefit definitions for each stakeholder (b_c and b_r). These definitions need to be standardised for comparing demand response programs across the world. Research specifically focusing on standardising definitions of cost-benefits for different stakeholders and the economic advantage of different baselines presents a huge area of research that is yet to be explored. It is recommended that focus be placed in that area to enhance and add value to the current state of-the-art.

6.2.5 Response Fatigue

This research assumed that demand response is provided continuously by the household. However, further research can be done to modify the model to address intermittent demand response events and their effects on customer and retailer costs and benefits. One approach to doing this is to introduce a "Response Fatigue Index" [53] to measure how long the customer is capable of abiding by the operation of the residential energy management system before they are tired of using it. According to the index there are two important factors that affect response fatigue: the frequency of demand response signals and duration of each demand response event. The index is given in Equation (6.1).

$$RFI = 100\% \times \sum_{h=1}^{N_h} \left[\pi_h \times \left(\frac{\sum_{i=1}^{N_i} v_i \times \tau_{i,h}}{T \times \sum_{i=1}^{N_i} v_i} \right) \right] \tag{6.1}$$

where

RFI	Response Fatigue Index
π_h	Scenario probability
N_h	Number of scenarios
v_i	Willingness of users to modify consumption
$\tau_{i,h}$	Duration that the customer is dissatisfied
T	Operation time of appliance "i"

Having a "Response Fatigue Index" to measure the interaction between the customer and the device would be useful in highlighting how customer behaviour changes over time.

Having achieved the overarching goal of the research, making several major contributions to the state of the art and giving recommendations for future research, this work has fulfilled its purpose.

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Appendices

The appendices provided in this section are meant to provide supplemental information to support the contents of this thesis. Where necessary the appendices provide extra information, results and analysis to help the reader gain a more thorough understanding of the concepts involved in the narrative of the research.

Appendix A. Description of customers from the "Low Carbon" London project

Table A.1. Description of customer groups from the "Low Carbon London" Project

Meta-Groups	Type	Description
Affluent	Lavish Lifestyles	These are the most affluent people in the UK such as premiership footballers, hedge fund managers, entrepreneurs, people in high status senior managerial and professional positions and very well-educated individuals.
	Executive Wealth	Wealthy families living in larger detached or semi-detached properties either in the suburbs, the edge of towns or in semi-rural locations.
	Mature Money	These people tend to be older empty nesters and retired couples. Many live-in rural towns and villages, others live in the suburbs of larger towns.
	City Sophisticates	Affluent younger professionals, metropolitan professionals and socialising young renters who generally own flats in major towns and cities.
	Career Climbers	Younger people, singles, couples and families with young children. They live in flats, apartments and smaller houses, which they are sometimes renting and often buying with a mortgage, occasionally using a shared equity scheme.
Comfortable	Countryside Communities	Areas of the lowest population densities in the country, ranging from remote farming areas to smaller villages and housing on the outskirts of smaller towns. Housing is typically owner occupied, detached or semi-detached with some renting.
	Successful Suburbs	Comprises home-owning families living comfortably in stable areas in suburban and semi-rural locations. They mainly live in three or four bedrooms detached and semi-detached homes of an average value for the locality.
	Steady Neighbourhoods	Home-owning families, often middle–aged, are living comfortably in suburban and urban locations.
	Comfortable Seniors	established communities are generally made up of retired and older empty nester couples.
	Starting out	Couples in their first home, starting a family, and others who are at an early stage of their career. Some are still renting but most will be buying their home with a mortgage.
	Student life	Areas dominated by students and young people, often recent graduates.
	Modest Means	People own or rent smaller older terraced housing and flats, which often includes some of the least expensive housing in the area. The mix of families is likely to include singles, couples with children and single parents and with a younger than average age profile.

Table A.1. continued…

Meta-Groups	Type	Description
Adversity	. Striving Families	low income families typically live on traditional low-rise estates.
	Poorer Pensioners	Pensioners and older people the majority of which are renting social housing but there are a few who own their home or rent privately.
	Young Hardship	Younger people who own or rent cheap small terraced houses or flats.
	Struggling Estates	Low income families living on traditional urban estates.
	Difficult Circumstances	These are streets with a higher proportion of younger people. Although all age groups may be represented those aged under 35 and with young children are more prevalent.
	Not Private Households	These people may be in communal establishments yet still consumers to some degree. This includes defence establishments, hotels, hostels, children's homes, refuges and local authority accommodation for travellers.

Appendix B. Typical monthly load profiles for the 36 customer groups

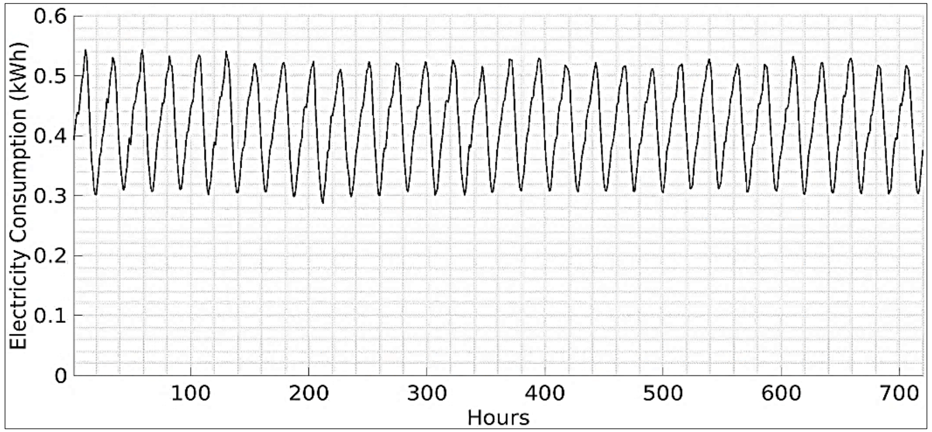

Figure B.1. Average monthly load profile for “Lavish Lifestyle” customers paying a Flat-rate tariff

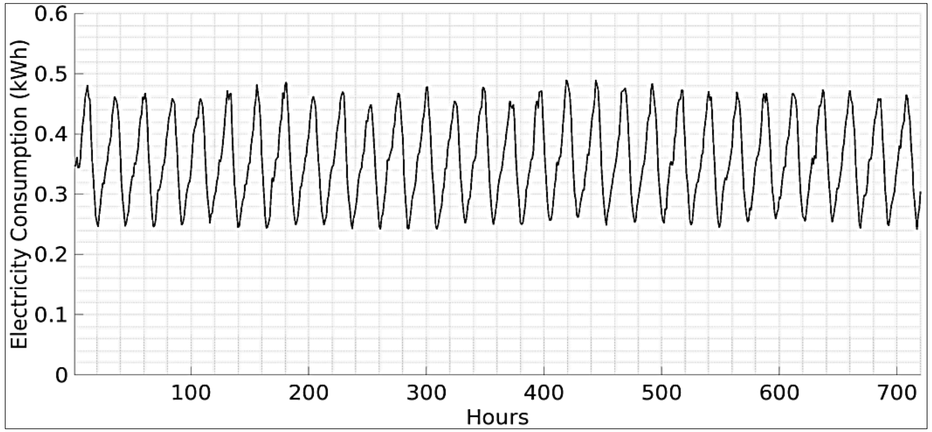

Figure B.2. Average monthly load profile for “Lavish Lifestyle” customers paying a Time-Of-Use tariff

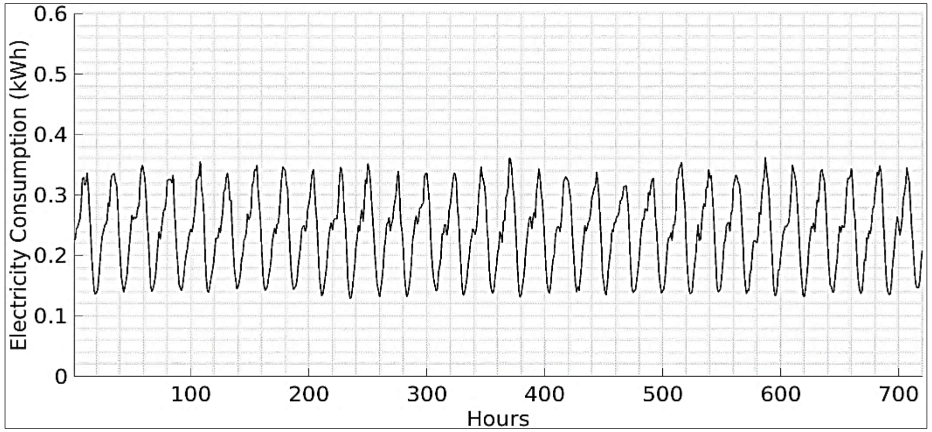

Figure B.3. Average monthly load profile for “Executive Wealth” customers paying a Flat-rate tariff

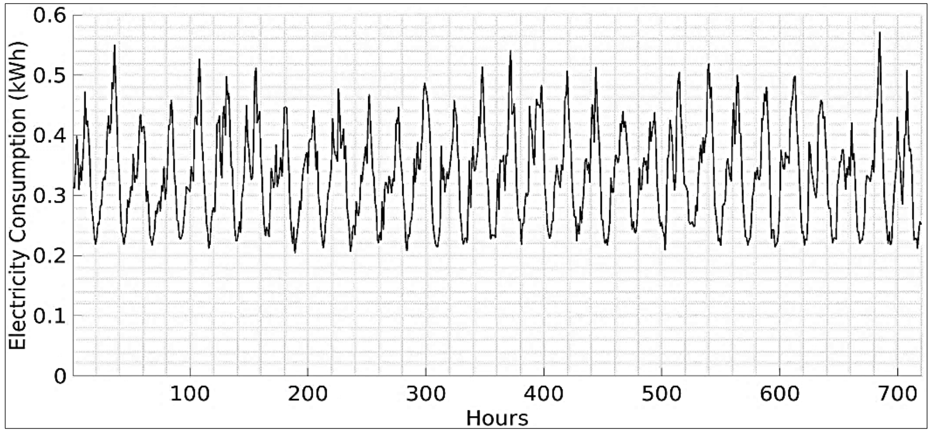

Figure B.4. Average monthly load profile for “Executive Wealth” customers paying a Time-Of-Use tariff

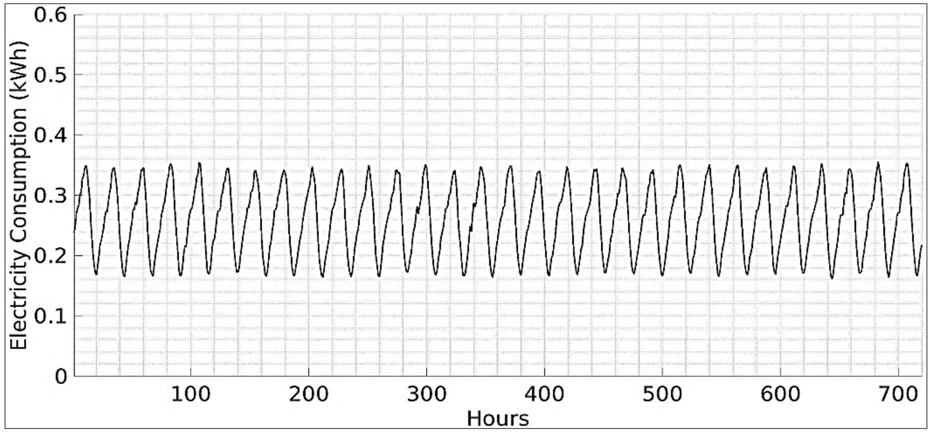

Figure B.5. Average monthly load profile for "Mature Money" customers paying a Flat-rate tariff

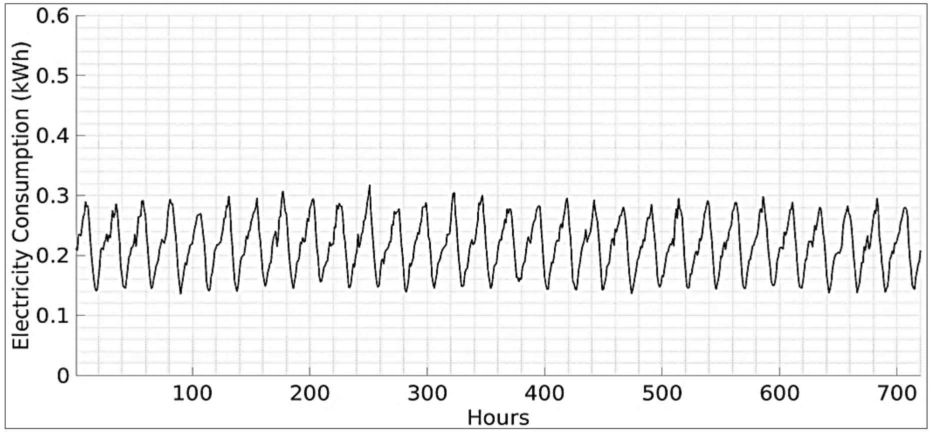

Figure B.6. Average monthly load profile for "Mature Money" customers paying a Time-Of-Use tariff

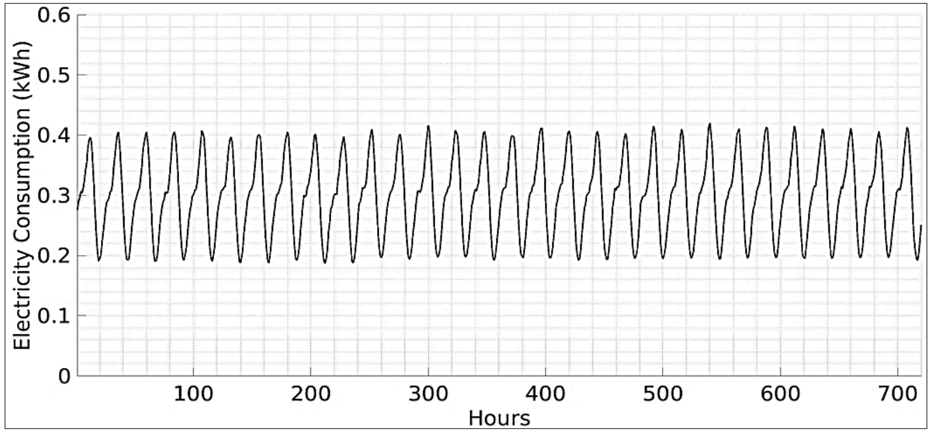

Figure B.7. Average monthly load profile for "City Sophisticates" customers paying a Flat-rate tariff

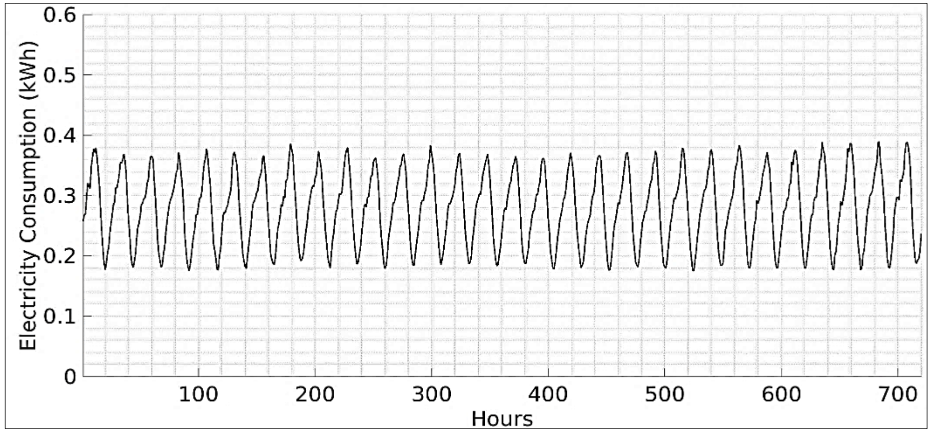

Figure B.8. Average monthly load profile for "City Sophisticates" customers paying a Time-Of-Use tariff

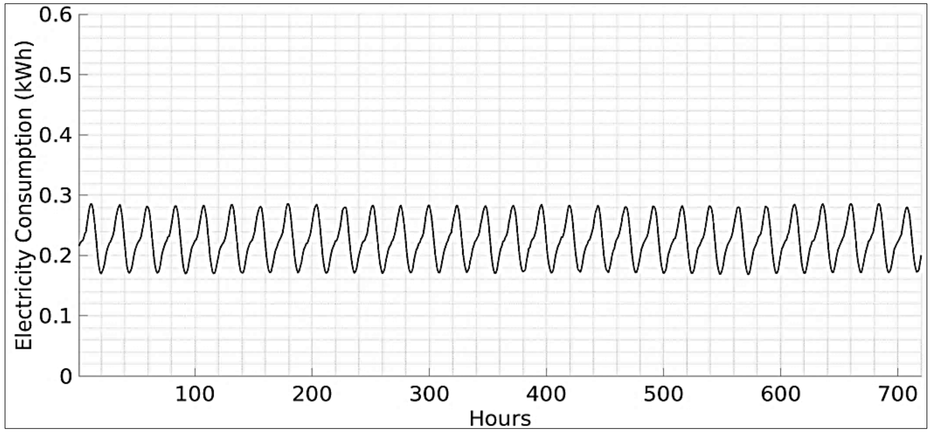

Figure B.9. Average monthly load profile for “Career Climbers” customers paying a Flat-rate tariff

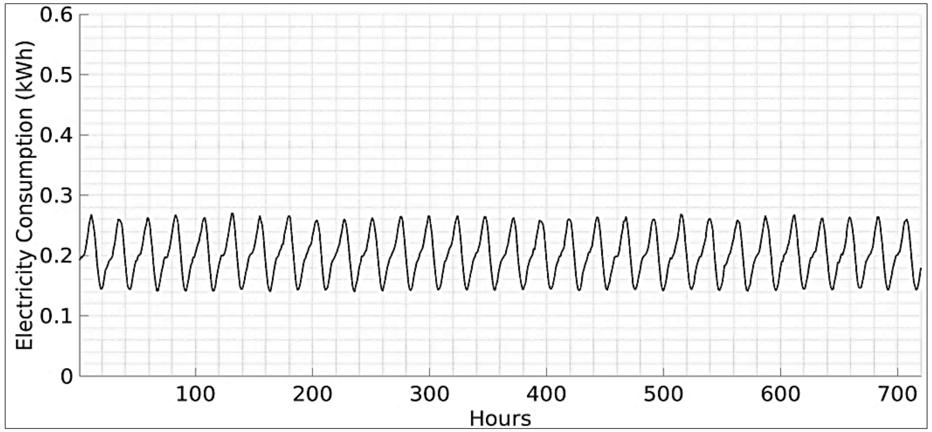

Figure B.10. Average monthly load profile for “Career Climbers” customers paying a Time-Of-Use tariff

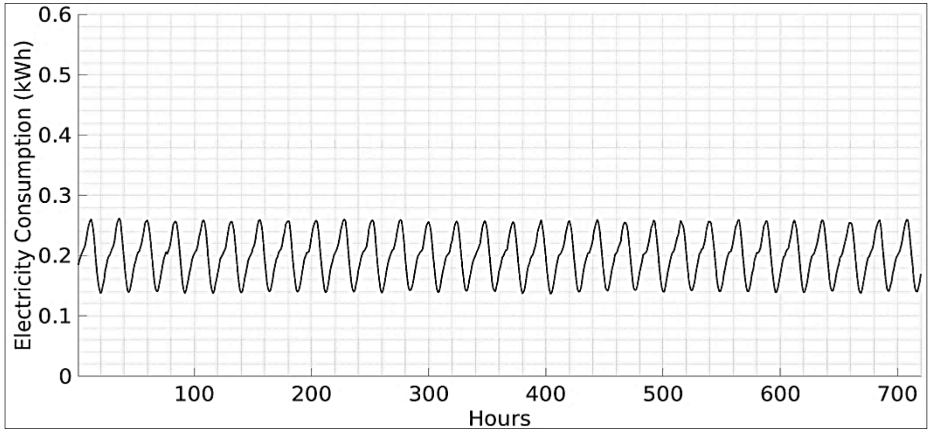

Figure B.11. Average monthly load profile for “Countryside Communities” customers paying a Flat-rate tariff

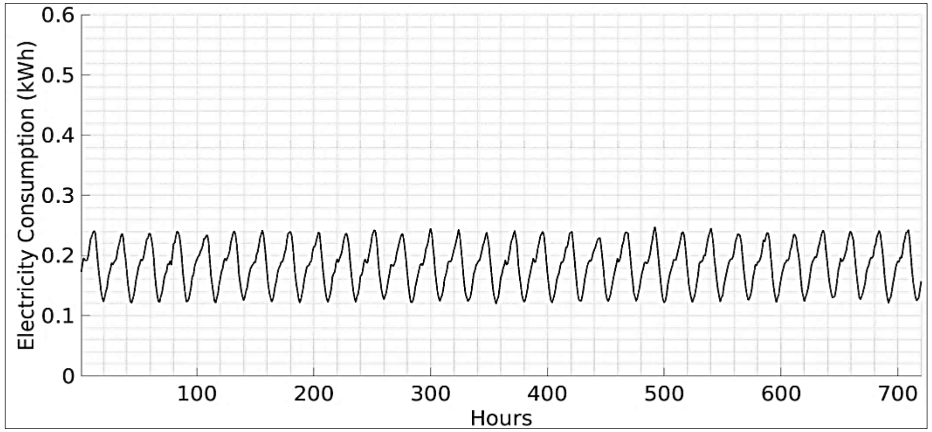

Figure B.12. Average monthly load profile for “Countryside Communities” customers paying a Time-Of-Use tariff

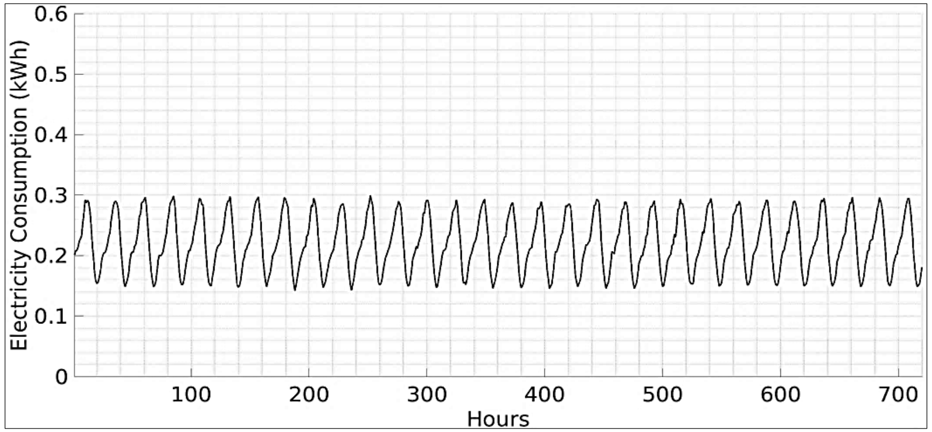

Figure B.13. Average monthly load profile for “Successful Suburbs” customers paying a Flat-rate tariff

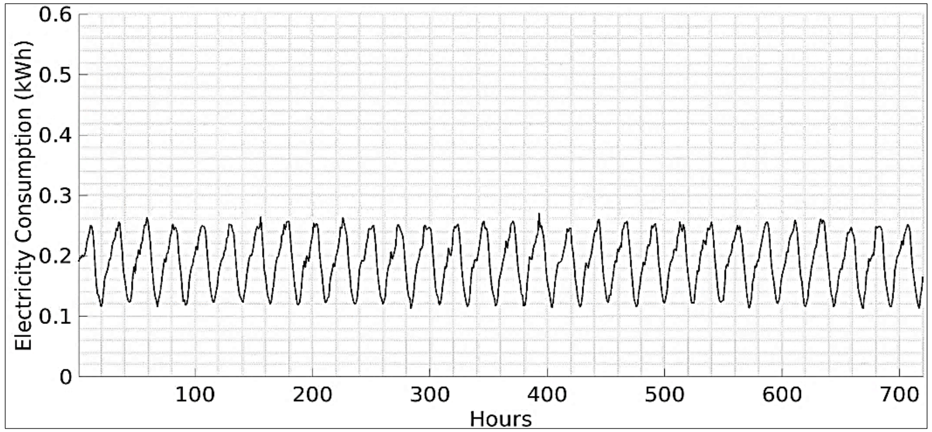

Figure B.14. Average monthly load profile for “Successful Suburbs” customers paying a Time-Of-Use tariff

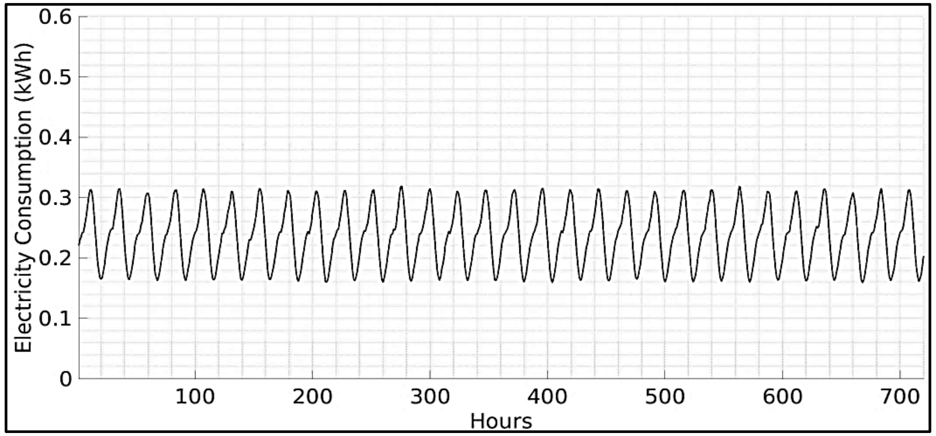

Figure B.15. Average monthly load profile for “Steady Neighbourhoods” customers paying a Flat-rate tariff

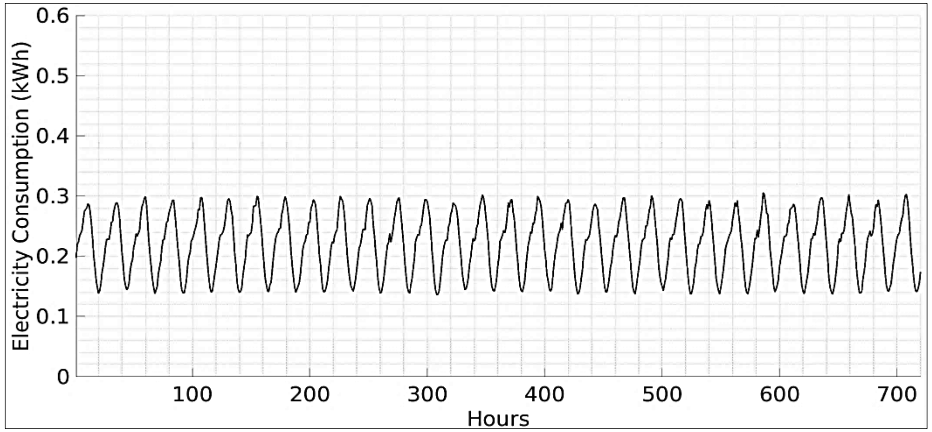

Figure B.16. Average monthly load profile for “Steady Neighbourhoods” customers paying a Time-Of-Use tariff

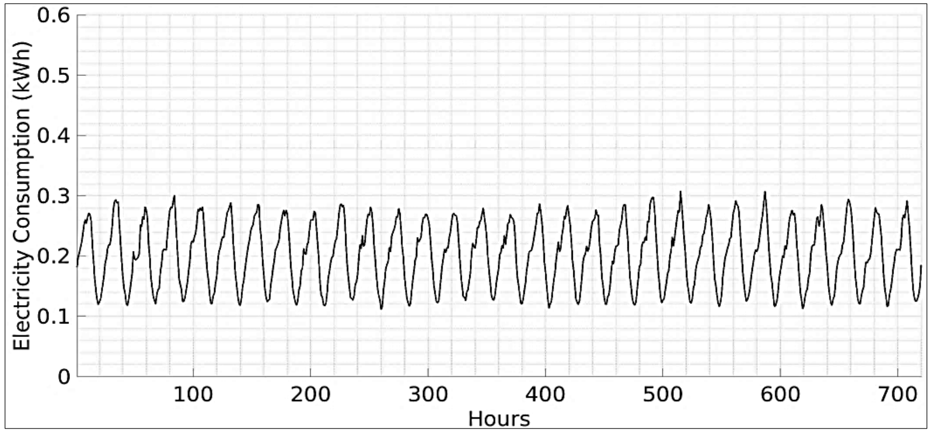

Figure B.17. Average monthly load profile for “Comfortable Seniors” customers paying a Flat-rate tariff

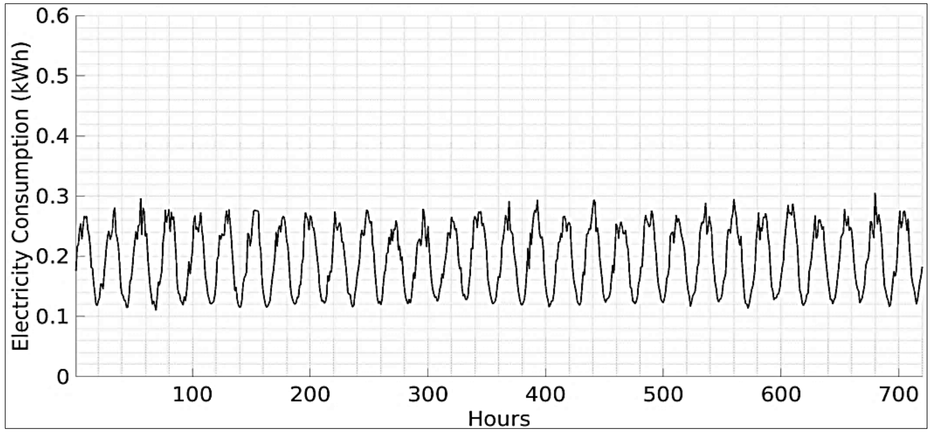

Figure B.18. Average monthly load profile for “Comfortable Seniors” customers paying a Time-Of-Use tariff

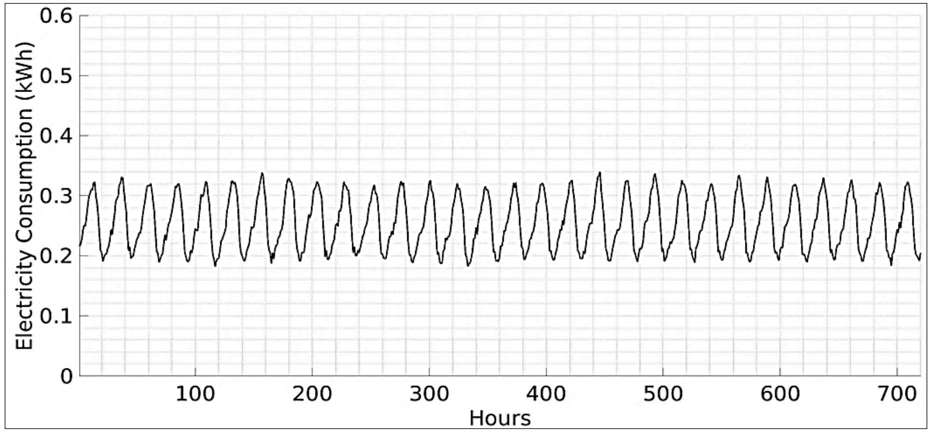

Figure B.19. Average monthly load profile for “Starting out” customers paying a Flat-rate tariff

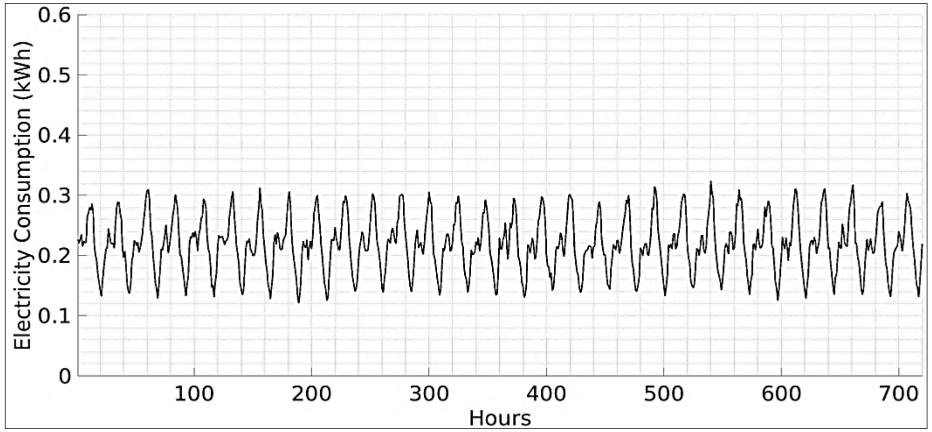

Figure B.20. Average monthly load profile for “Starting out” customers paying a Time-Of-Use tariff

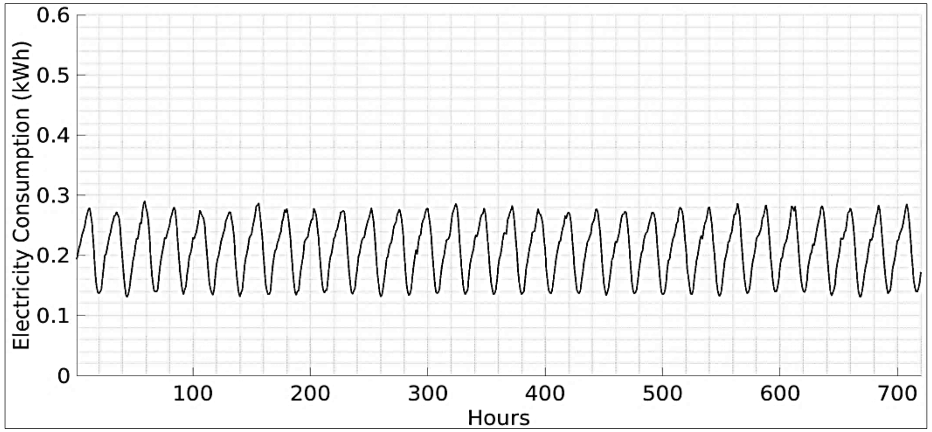

Figure B.21. Average monthly load profile for “Student life” customers paying a Flat-rate tariff

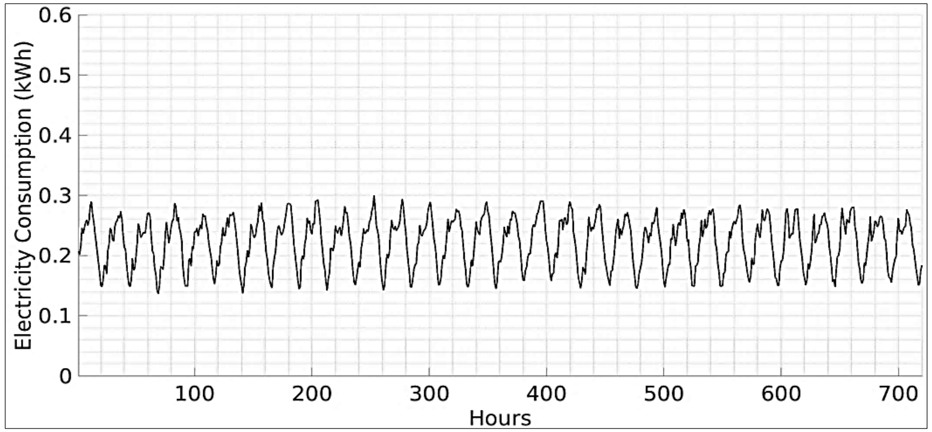

Figure B.22. Average monthly load profile for “Student life” customers paying a Time-Of-Use tariff

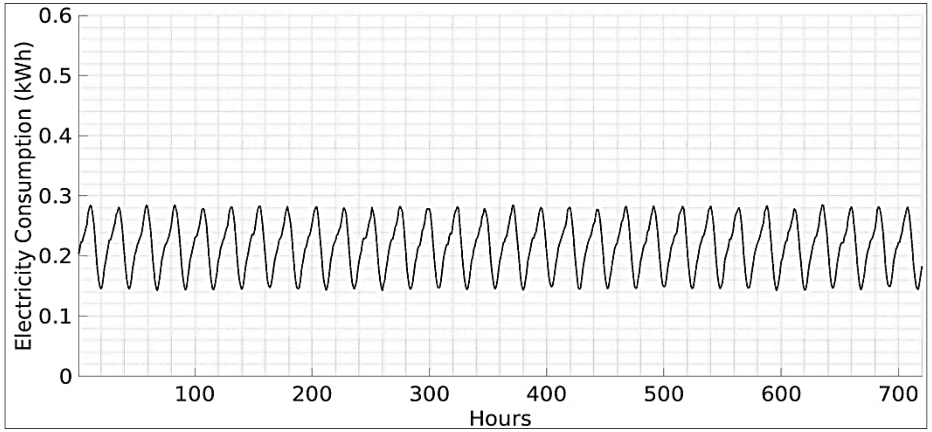

Figure B.23. Average monthly load profile for “Modest Means” customers paying a Flat-rate tariff

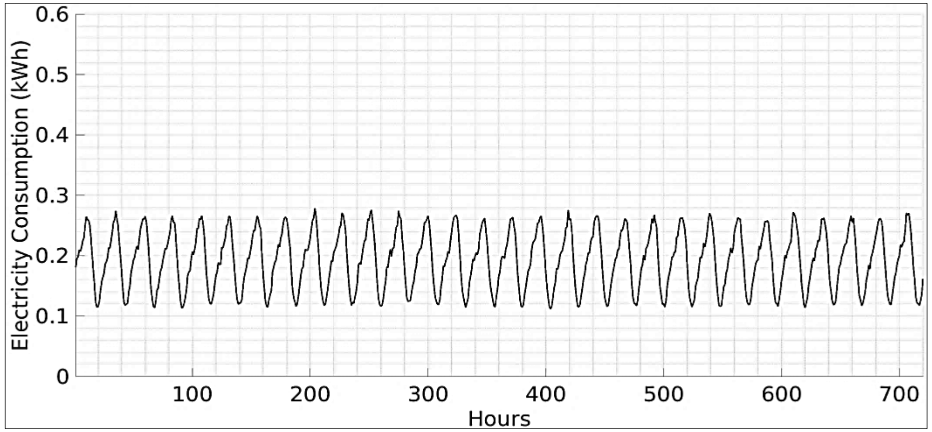

Figure B.24. Average monthly load profile for “Modest Means” customers paying a Time-Of-Use tariff

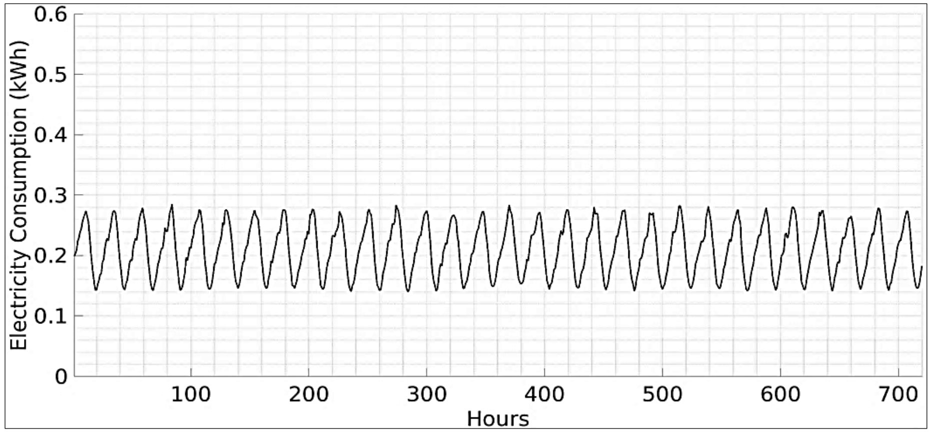

Figure B.25. Average monthly load profile for "Striving Families" customers paying a Flat-rate tariff

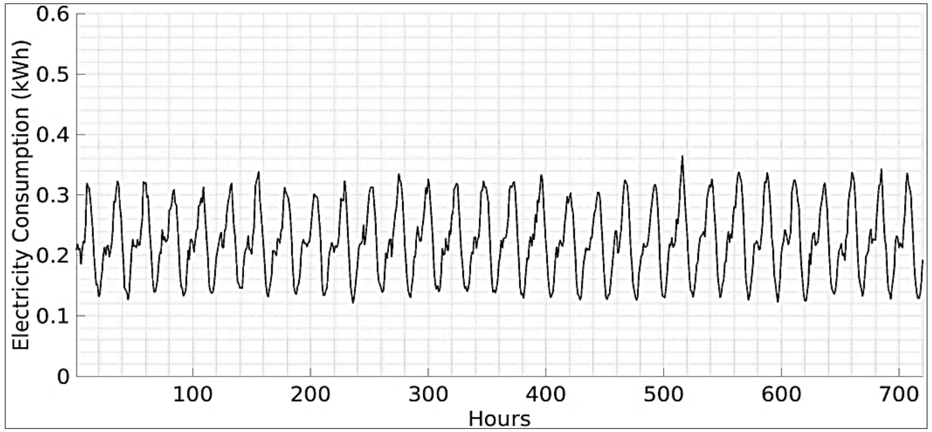

Figure B.26. Average monthly load profile for "Striving Families" customers paying a Time-Of-Use tariff

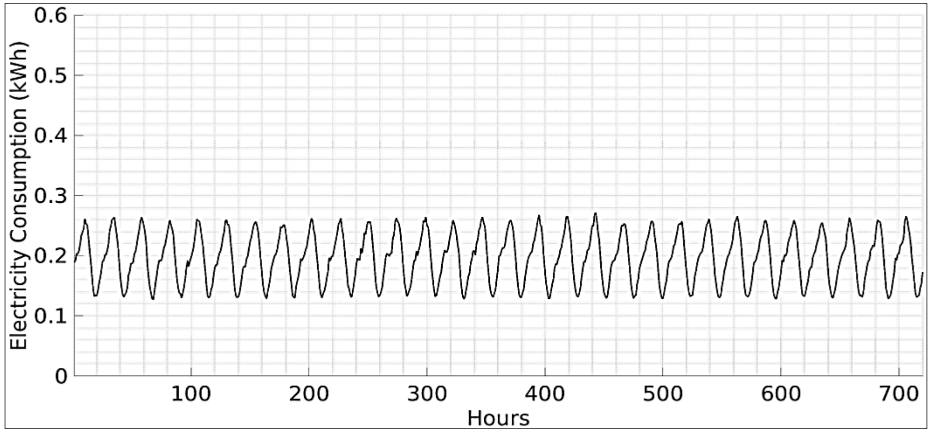

Figure B.27. Average monthly load profile for "Poorer Pensioners" customers paying a Flat-rate tariff

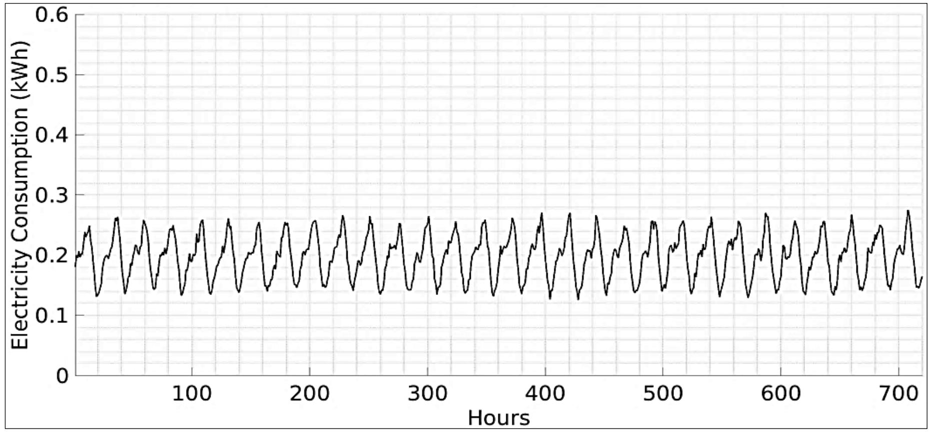

Figure B.28. Average monthly load profile for "Poorer Pensioners" customers paying a Time-Of-Use tariff

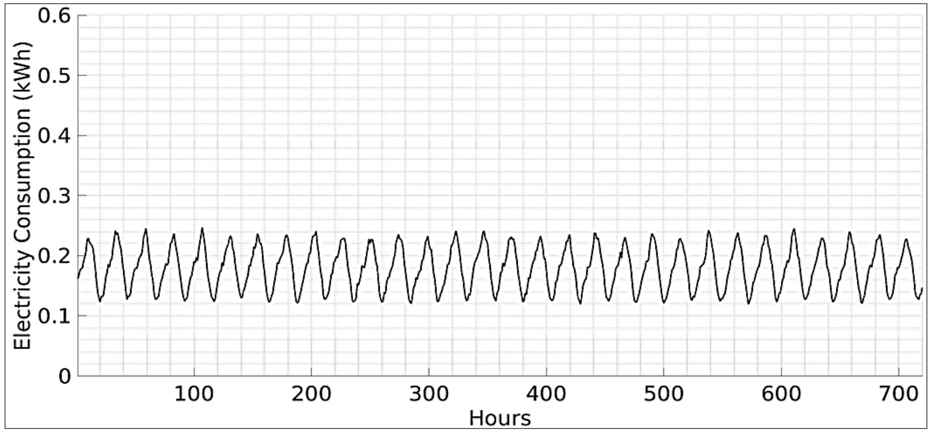

Figure B.29. Average monthly load profile for “Young Hardship” customers paying a Flat-rate tariff

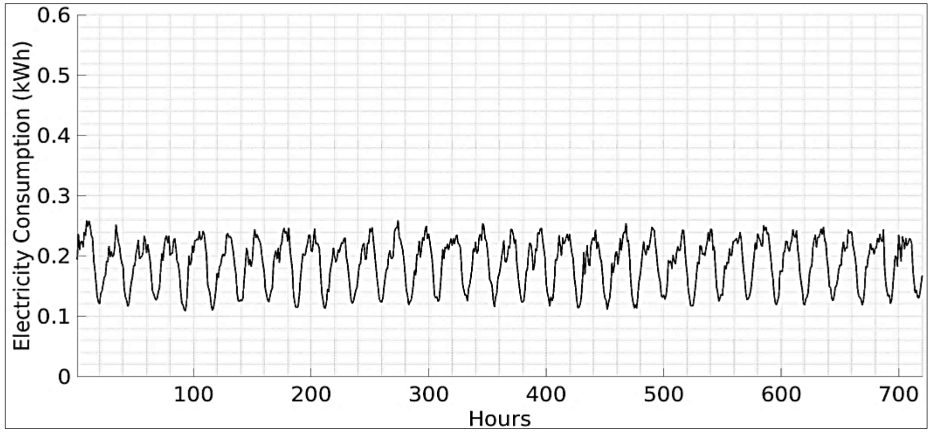

Figure B.30. Average monthly load profile for “Young Hardship” customers paying a Time-Of-Use tariff

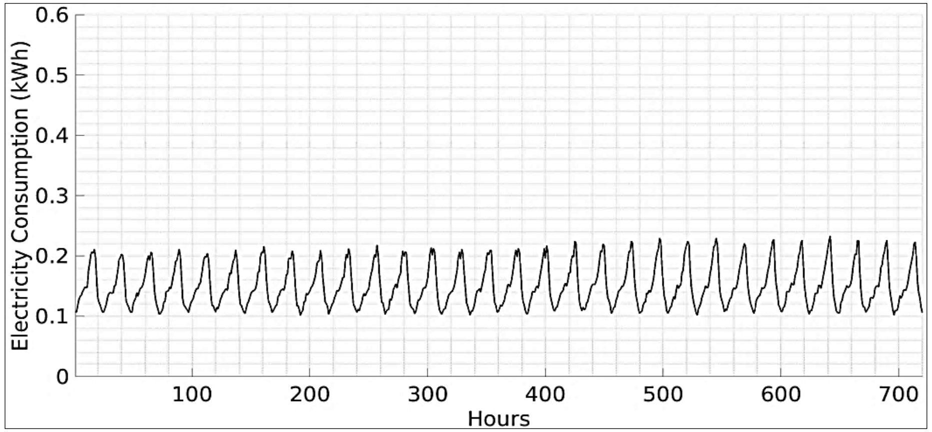

Figure B.31. Average monthly load profile for “Struggling Estates” customers paying a Flat-rate tariff

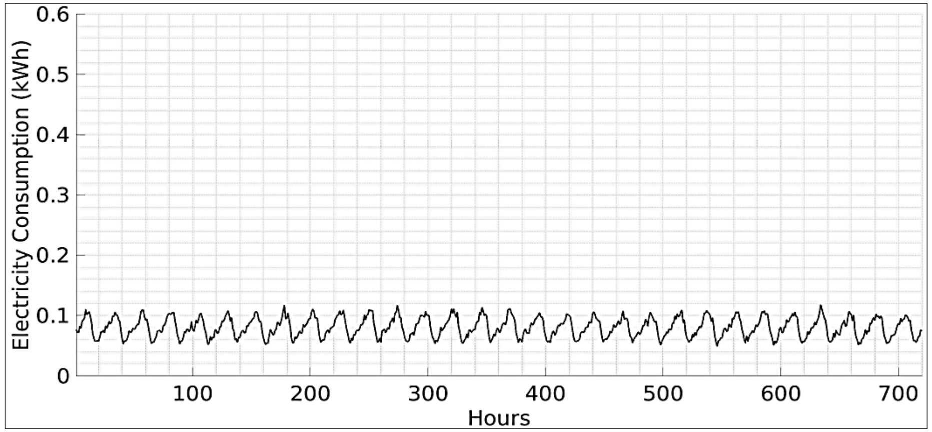

Figure B.32. Average monthly load profile for “Struggling Estates” customers paying a Time-Of-Use tariff

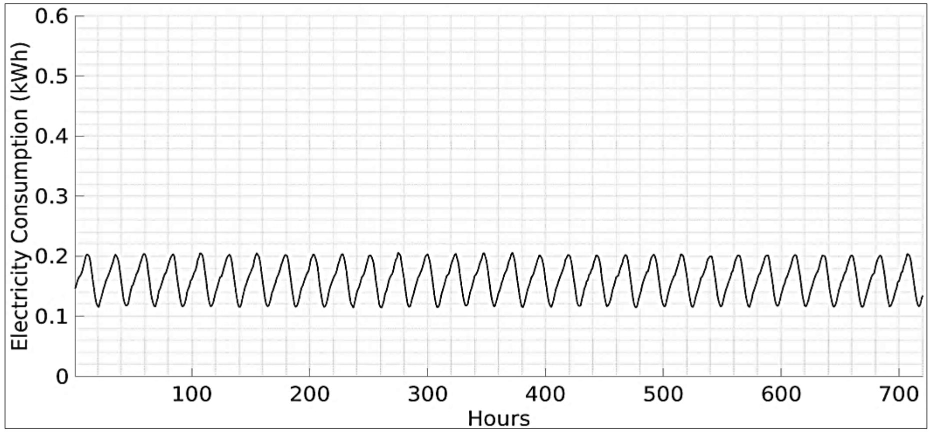

Figure B.33. Average monthly load profile for “Difficult Circumstances” customers paying a Flat-rate tariff

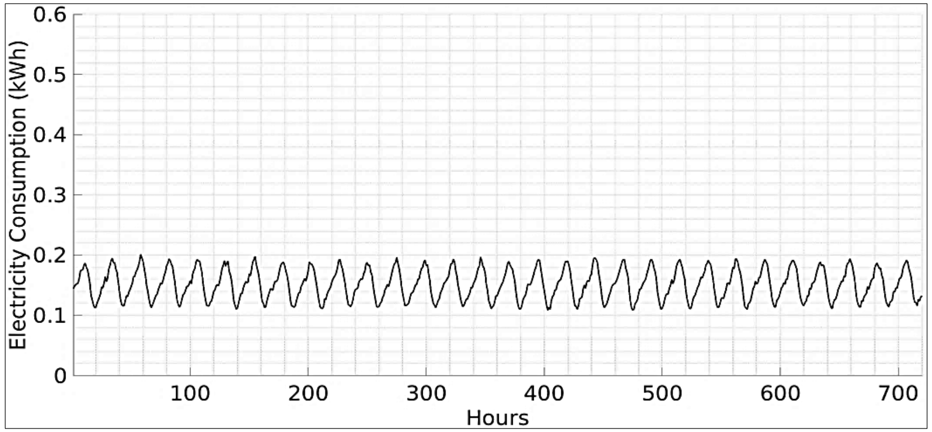

Figure B.34. Average monthly load profile for “Difficult Circumstances” customers paying a Time-Of-Use tariff

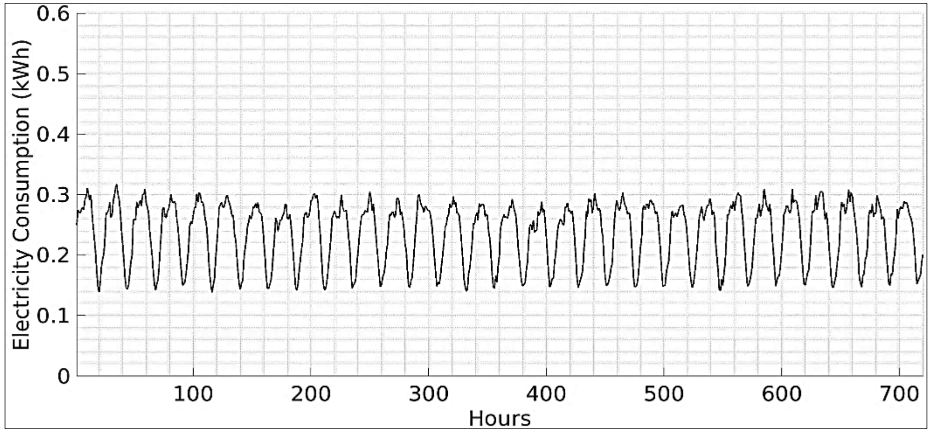

Figure B.35. Average monthly load profile for “Not Private Households” customers paying a Flat-rate tariff

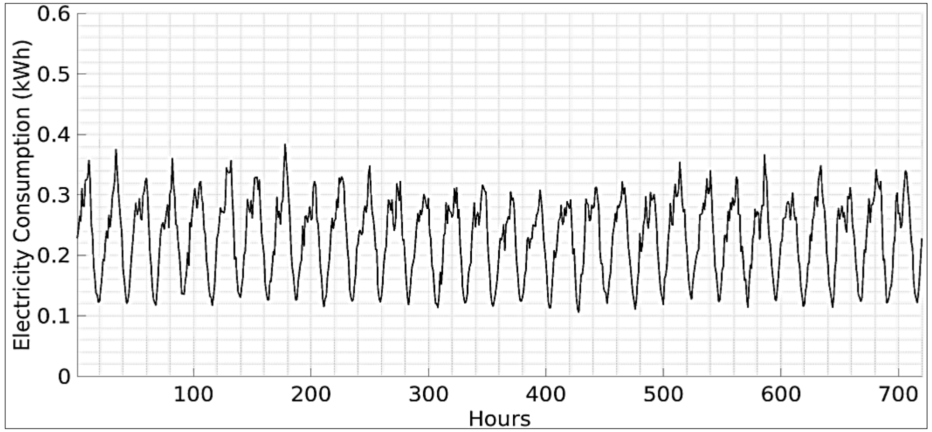

Figure B.36. Average monthly load profile for “Not Private Households” customers paying a Time-Of-Use tariff

Appendix C. Proving that the objective function b_c has a global maximum

The objective function presented in Equation (3.7) is determines the amount of demand response provided by the residential energy management system. Very function (J_1 to J_6) is dependent on the value of d_t^*, the forecasted demand of the household after the demand response event. It is necessary to show that there are conditions under which this function has a global maximum value. To do this, the derivative of the function can be used. Consider the Equation (3.7) (restated below).

$$Maximize\ b_c = \frac{w_1.J_1 + w_2.J_2 + w_3.J_3 + w_4.J_4}{w_5.J_5 + w_6.J_6} \tag{3.7}$$

This equation has the form shown in Equation (C.1).

$$b_c = \frac{Y_n}{Y_d} \tag{C.1}$$

Where Y_n is the numerator of Equation (3.7) and Y_d is the denominator of Equation (3.7). It is important to note that Y_n can result in both negative and positive values depending on the values d_t^* has. In addition, Y_d results in strictly positive values (see Table) irrespective of the values d_t^* has. Equation (C.1) can be differentiated to obtain Equation (C.2).

$$b_c{}' = \frac{Y_d.Y_n{}' - Y_n.Y_d{}'}{(Y_d)^2} \tag{C.2}$$

Equation (C.2) represents the derivative of the cost-benefit for the customer. For the function b_c to have a point of maximum (or minimum) called a saddle point, Equation (C.2) must be equal to zero. This is shown in Equation (C.1).

$$\frac{Y_d.Y_n{}' - Y_n.Y_d{}'}{(Y_d)^2} = 0 \tag{C.3}$$

For the objective function b_c to have a strictly maximum global value, the second order derivative of Equation (C.2) must be less than zero. This is shown in Inequality (C.4).

$$\frac{(Y_d)^2[(Y_d.Y_n'' + Y_d'.Y_n') - (Y_n.Y_d'' + Y_n'.Y_d')] - 2.(Y_d.Y_n' - Y_n.Y_d').Y_d}{(Y_d)^4} < 0 \tag{C.4}$$

Inequality (C.4) can be simplified as shown in Inequality (C.5).

$$\frac{(Y_d.Y_n'' - Y_n.Y_d'')}{(Y_d)^2} - \frac{-2.(Y_d.Y_n' - Y_n.Y_d')}{(Y_d)^3} < 0 \tag{C.5}$$

Since Y_d results in strictly positive values irrespective of the values $d_t{}^*$, Inequality (C.5) can be multiplied by Y_d to get Inequality (C.6)

$$\frac{(Y_d.Y_n'' - Y_n.Y_d'')}{Y_d} < -2.\frac{(Y_d.Y_n' - Y_n.Y_d')}{(Y_d)^2} \tag{C.6}$$

Equation (C.1) can be substituted in Inequality (C.6) to get Inequality (C.7).

$$\frac{(-Y_d.Y_n'' + Y_n.Y_d'')}{Y_d} > 2.(0) \tag{C.7}$$

Since Y_d results in strictly positive values irrespective of the values $d_t{}^*$, Inequality (C.7) can be multiplied by Y_d to get Inequality (C.8).

$$-Y_d.Y_n'' + Y_n.Y_d'' > 0 \tag{C.8}$$

Inequality (C.8) can be rewritten as shown in Inequality (C.9).

$$\frac{Y_n}{Y_d} > \frac{Y_n''}{Y_d''} \tag{C.9}$$

Inequality (C.9) can be rewritten as shown in Inequality (C.10).

$$b_c > \frac{Y_n''}{Y_d''} \tag{C.10}$$

Inequality (C.10) is a condition that must be satisfied in order for the objective function given be Equation (3.7) to have a global maximum value. Now finding the double derivative of the functions in the numerator of b_c indicates that $Y_n'' = 0$. Therefore, Inequality (C.10) can be rewritten as Inequality (C.11).

$$b_c > 0 \tag{C.11}$$

Inequality (C.11) represents the condition that must hold in order for the function given in Equation (3.7) to have a global maximum.

Table provides the derivatives of the objective functions from Equation (3.7) with respect to the reduced household hourly demand (d_t^*). These derivatives provide support for the result found for Inequality (C.11).

Table C.1. Derivatives of the objective functions from Equation (3.7)

Function	1st derivative	2nd derivative
$J_1 = \sum_{t=1}^{T}[(d_t - d_t^*) \times r_t]$	$J_1' = \sum_{t=1}^{T}[-r_t]$	$J_1'' = 0$
$J_2 = \sum_{t=1}^{T}[(d_t - d_t^*) \times c \times c_r]$	$J_2' = \sum_{t=1}^{T}[-c \times c_r]$	$J_2'' = 0$
$J_3 = \sum_{t=1}^{T}(\tau . d_t - \tilde{\tau} . d_t^*)$	$J_3' = \sum_{t=1}^{T} -\tilde{\tau}$	$J_3'' = 0$
$J_4 = \sum_{t=1}^{T}[(d_t - d_t^*) \times (r_t - s_t)]$	$J_4' = \sum_{t=1}^{T}[-(r_t - s_t)]$	$J_4'' = 0$
$J_5 = X \times \frac{Y}{Z}$	$J_5' = \frac{X}{Z} \times Y'$	$J_5'' = \frac{X}{Z} \times Y''$
$J_6 = \delta(p_p . J_1 - C_p)^2$	$J_6' = 2 \times \delta \times p_p . J_1' \times (p_p . J_1 - C_p)^1$	$J_6'' = 2 \times \delta \times (p_p)^2 \times J_1'$
Y_n	$Y_n' = w_1 J_1' + w_2 J_2' + w_3 J_3' + w_4 J_4'$	$Y_n'' = 0$
Y_d	$Y_d' = w_5 J_5' + w_6 J_6'$	$Y_d'' = w_5 J_5'' + w_6 J_6''$

where
$X = \sum_{t=1}^{T}[d_t \times r_t]$
$Y = \sigma^2{}_t^{*} + \sum_{t=1}^{T}[(d_t^*)^2]$
$Z = \sigma^2{}_t + \sum_{t=1}^{T}[d_t^2]$

Appendix D. Demand response models for different types of loads in a household

Table D.1. Demand response models for different types of loads in a household [106]

Load types	Equations representing load types	Technical Explanation
Single period elastic load	$d_S(i) = d_0(i).\left(\frac{\rho(i) + A(i) + pen(i)}{\rho_0(i)}\right)^{E(i,i)}$	The equation expresses the change in demand as a function of self-elasticity. Self-elasticity $E(i,i)$ measures responsiveness of electricity demand in period "i" to the change in the electricity tariff for that same period.
Multiple period elastic Load	$d_M(i) = d_0(i).EXP\left\{\sum_{\substack{j=1 \\ j\neq i}}^{T} E(i,j)ln\left(\frac{\rho(j) + A(j) + pen(j)}{\rho_0(j)}\right)\right\}$	The equation expresses the change in demand as a function of cross-elasticity. Cross-elasticity $E(i,j)$ measures responsiveness of electricity demand in period "i" to the change in the electricity tariff during period "j".
Composite elastic load	$d_C(i) = d_0(i).EXP\left\{\sum_{j=1}^{T} E(i,j)ln\left(\frac{\rho(j) + A(j) + pen(j)}{\rho_0(j)}\right)\right\}$	The equation expresses the change in demand as a function of cross-elasticity. Cross-elasticity $E(i,j)$ measures responsiveness of electricity demand in period "i" to the change in the electricity tariff during period "j".

where

ρ_0	Initial price within a certain period
d_0	Initial demand within a certain period
∂d	Difference in demand between two periods
$\partial \rho$	Difference in price between two periods
$E(i,i)$	Self-elasticity within period *i*
$E(i,j)$	Cross elasticity between period *i* and *j*
$A(j)$	Incentive received by customer for reducing demand during period *j*
$pen(j)$	Penalty for not reducing demand during period *j*

For this research $A(j) = 0$ and $pen(j) = 0$ for all $A(j)$ and $pen(j)$. Incentives ($A(j)$) and penalties ($pen(j)$) provided by an electricity retailer is heavily dependent on the portfolio goals and strategies of the retailer. Having $A(j) = 0$ and $pen(j) = 0$ for all $A(j)$ and $pen(j)$ simply means that very few assumptions are made about retailer portfolio or electricity market structure. This permitted the analysis to be general whilst still yielding substantial results.

Price elasticity of demand, $\mathrm{E}(\mathrm{a},\mathrm{b})$, shown in Table , is an economic measure that indicates by how much a customer is willing to change demand if price changes.

Table D.2. Price elasticity of demand [106]

	Equation representing elasticity
Price elasticity of demand	$E(a,b) = \frac{\rho_0}{d_0} \cdot \frac{\partial d}{\partial \rho} = \frac{\rho_0}{d_0} \cdot \frac{d_b - d_a}{p_b - p_a}$

where

$E(a,\mathrm{b})$	Elasticity between period a and b
∂d	Difference in demand between two periods
$\partial \rho$	Difference in price between two periods
d_a	Electricity demand during period "*a*"
d_b	Electricity demand during period "*b*"
ρ_a	Electricity tariff during period "*a*"
ρ_b	Electricity tariff during period "*b*"

The elasticity of demand can be found between two periods (cross-elasticity) or within a single period (self-elasticity).

Appendix E. Explanation of scenarios outlining possible combination of objectives for device

Table E.1. Scenarios outlining possible combination of objectives for device

Scenario Number	w_1	w_2	w_3	w_4	w_5	w_6	Explanation
1	0	0	0	0	1	1	Since w_1 to w_4 is zero, this means that the customer does not have the residential energy management system installed in the home. This is a base case.
2	1	0	0	0	1	1	Maximise customer savings whilst minimising customer discomfort and simple payback period.
3	0	1	0	0	1	1	Maximise emissions savings whilst minimising customer discomfort and simple payback period.
4	1	1	0	0	1	1	Maximise customer and emissions savings whilst minimising customer discomfort and simple payback period.
5	0	0	1	0	1	1	Maximise tax savings whilst minimising customer discomfort and simple payback period.
6	1	0	1	0	1	1	Maximise customer and tax savings whilst minimising customer discomfort and simple payback period.
7	0	1	1	0	1	1	Maximise emissions and tax savings whilst minimising customer discomfort and simple payback period.
8	1	1	1	0	1	1	Maximise customer, emissions and tax savings whilst minimising customer discomfort and simple payback period.
9	0	0	0	1	1	1	Maximise retail profit whilst minimising customer discomfort and simple payback period.
10	1	0	0	1	1	1	Maximise customer savings and retail profit whilst minimising customer discomfort and simple payback period.
11	0	1	0	1	1	1	Maximise emissions savings and retail profit whilst minimising customer discomfort and simple payback period.
12	1	1	0	1	1	1	Maximise customer savings, tax savings and retail profit whilst minimising customer discomfort and simple payback period.
13	0	0	1	1	1	1	Maximise tax savings and retail profit whilst minimising customer discomfort and simple payback period.
14	1	0	1	1	1	1	Maximise customer and tax savings and retail profit whilst minimising customer discomfort and simple payback period.
15	0	1	1	1	1	1	Maximise emissions and tax savings and retail profit whilst minimising customer discomfort and simple payback period.
16	1	1	1	1	1	1	Maximise customer, emissions and tax savings and retail profit whilst minimising customer discomfort and simple payback period.

Appendix F. Comparison of "Historical data" to all other baselines used in this research for a typical day for customers paying a Flat-Rate tariff

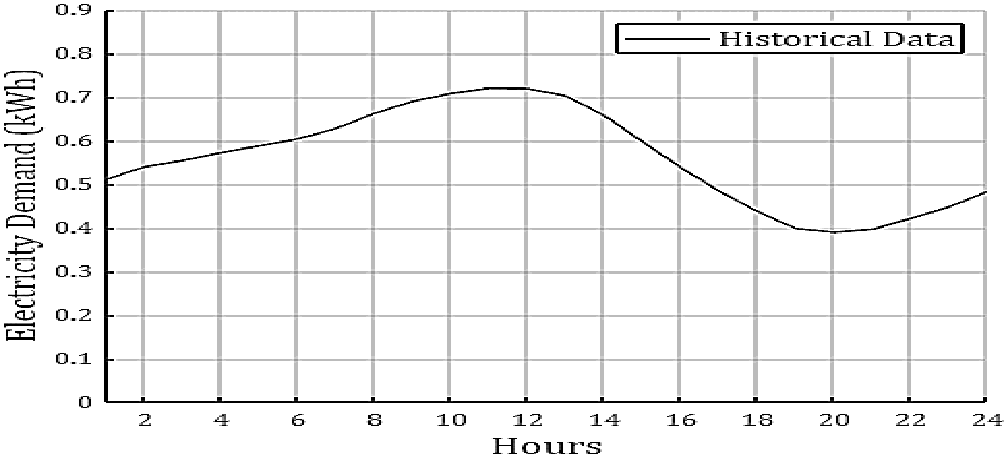

Figure F.1. "*Historical Data*" for a typical day for Flat-rate tariff customers

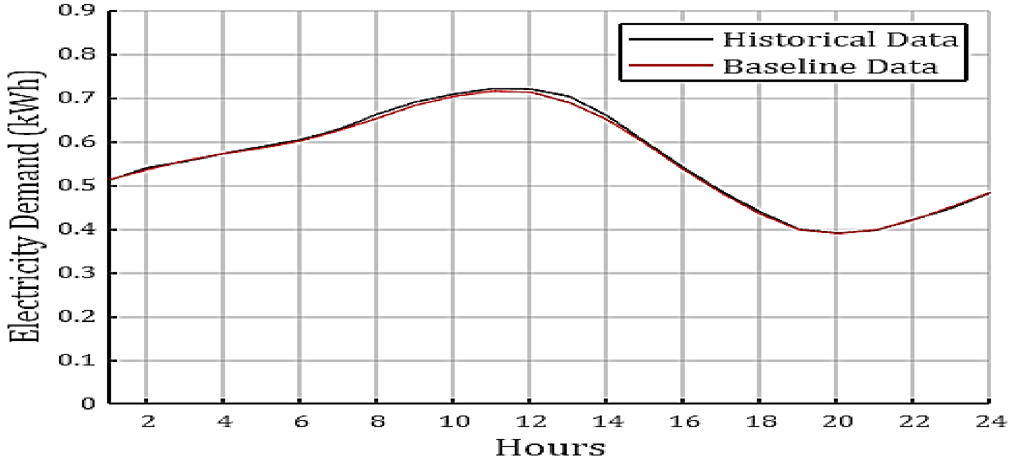

Figure F.2. "*Historical data*" and "*Last Y days*" baseline for Flat-rate customers

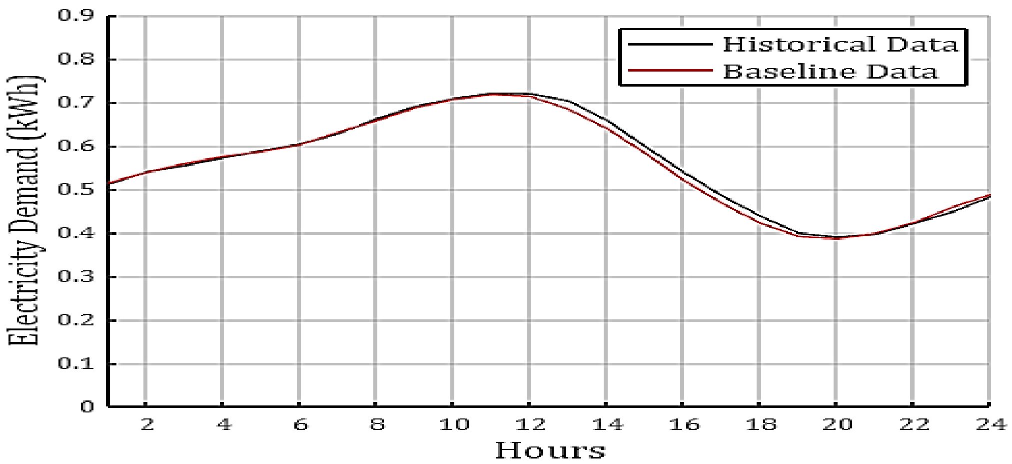

Figure F.3. “*Historical data”* and “*Low X of Y days”* baseline Flat-rate customers

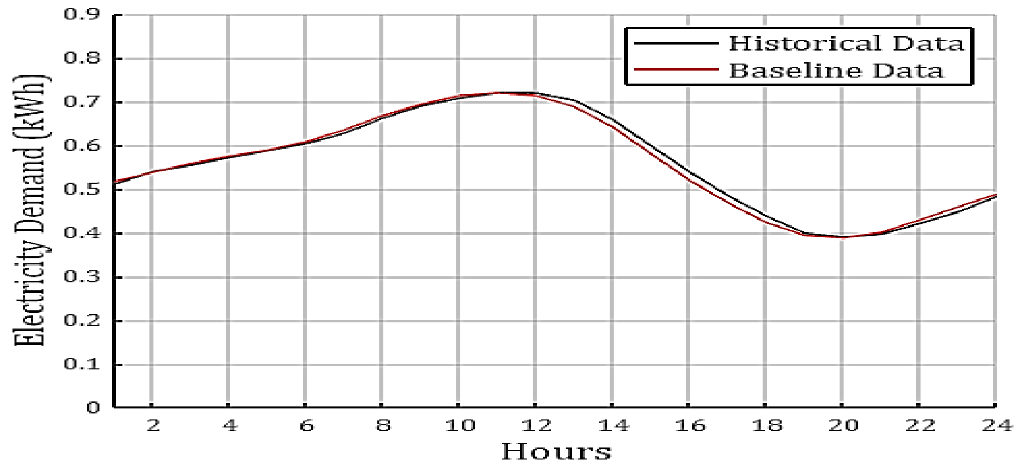

Figure F.4. “*Historical data*” and “*Mid X of Y days*” baseline for Flat-rate customers

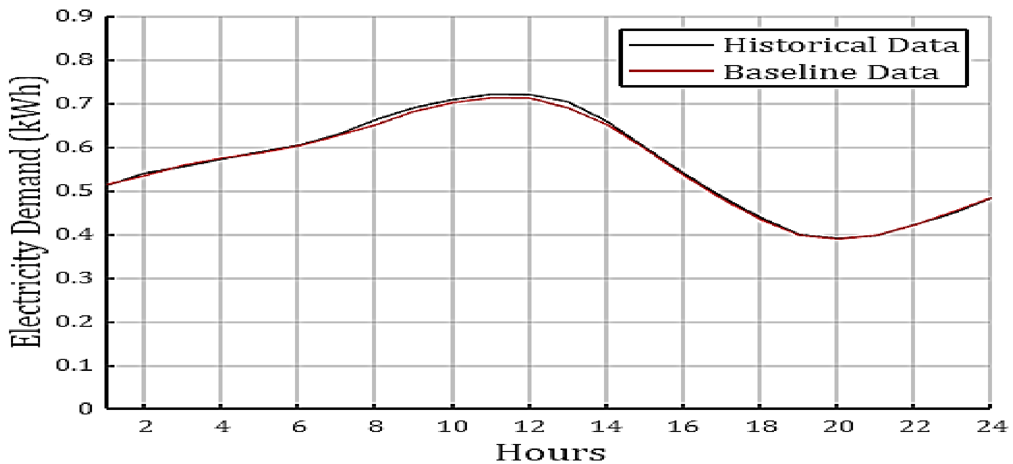

Figure F.6. “*Historical data*” and “*High X of Y days*” baseline for Flat-rate customers

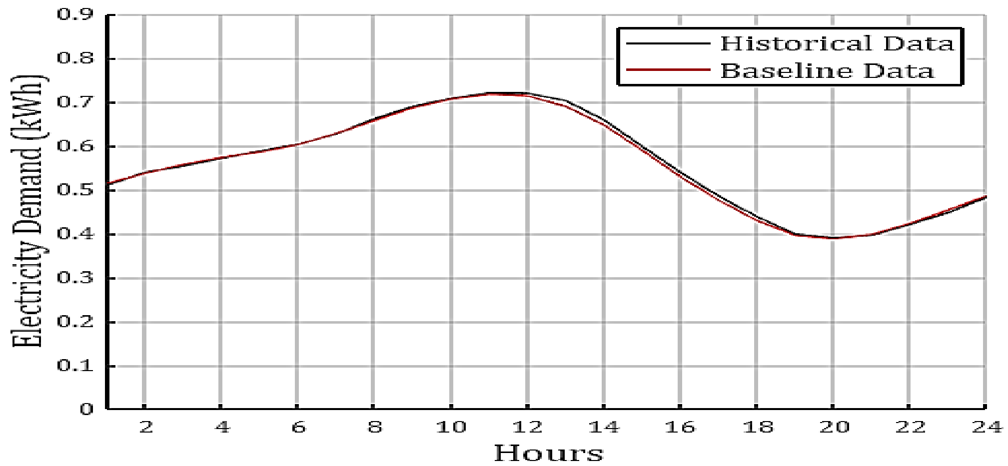

Figure F.7. “*Historical data*” and “*Exponential Moving Average*” baseline for Flat-rate customers

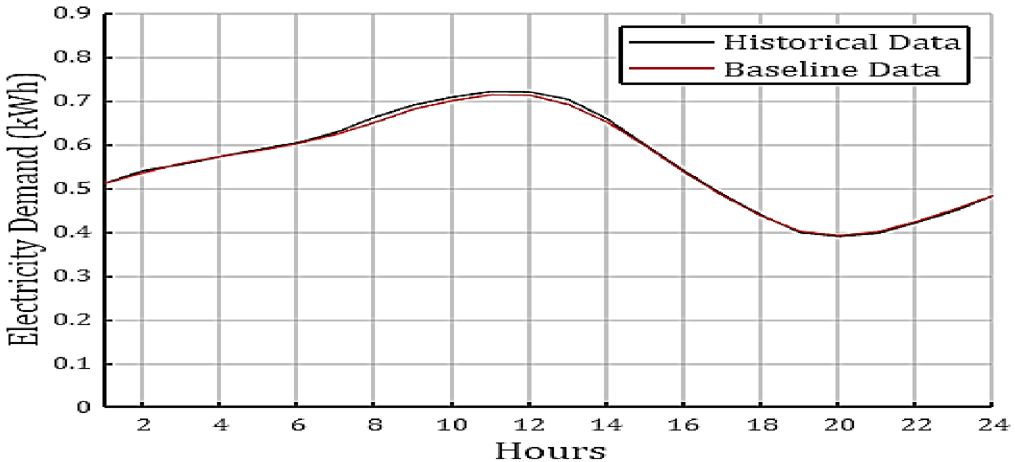

Figure F.8. “*Historical data*” and “*Linear Regression*” baseline for Flat-rate customers

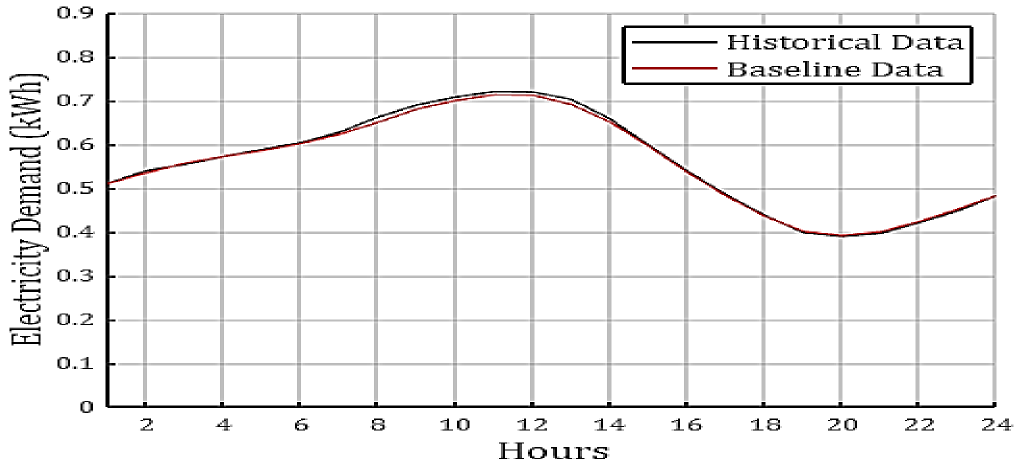

Figure F.9. “*Historical data*” and “*Polynomial Interpolation*” baseline for Flat-rate customers

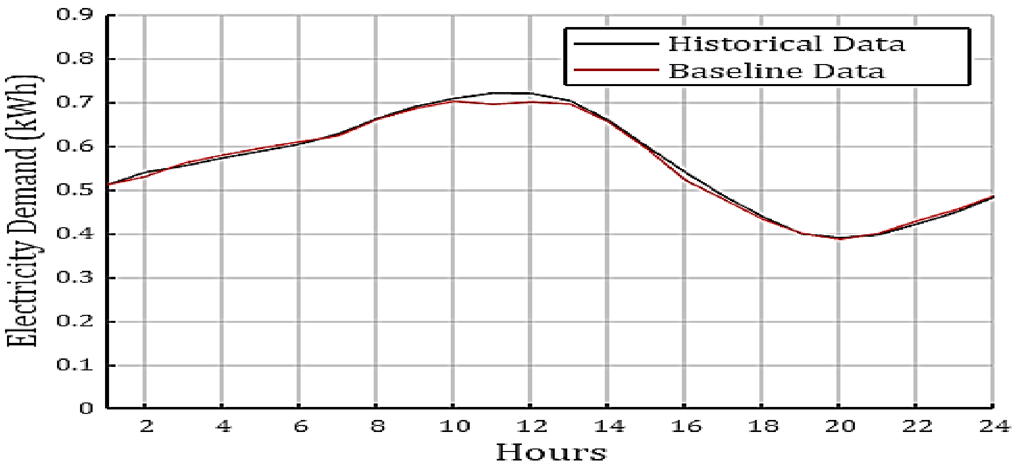

Figure F.10. “*Historical data*” and “*Neural Network*” baseline for Flat-rate customers

Appendix G. Formula for Log-likelihood function

The log-likelihood function, $ln(\hat{L})$, is the natural logarithm of the goodness of fit of a statistical model to a sample of data. The function is given by Equation (G.12).

$$ln(\hat{L}) = -\frac{n}{2}.ln(2\pi) - \frac{n}{2}.ln({\sigma_\varepsilon}^2) - \frac{1}{2{\sigma_\varepsilon}^2}.\sum_{i=1}^{n}(x_e - \mu)^2 \qquad \text{(G.12)}$$

where

$\hat{L}$	Likelihood function.
n	Number of data points used to calculate the model.
${\sigma_\varepsilon}^2$	Variance in the root-mean-square errors of the model
μ	Root-mean-square of the errors
x_e	Errors produced by the model

Appendix H. Economic advantage (E_A) of using different baselines

Table H.1. Economic advantage E_A of using "Historical Data" method to create a baseline for retailers and customers paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-2.590	-5.201	-2.279	1.827	1.674	5.726	0.585	-0.024	-0.022	-0.010	-0.016	-0.019	-0.020	-0.014	-0.017
City Sophisticates	0.000	-0.940	-0.694	5.768	0.320	0.175	0.089	0.051	-0.001	-0.006	-0.007	-0.006	-0.007	-0.002	-0.008	-0.004
Mature Money	0.000	-2.427	-3.096	-3.916	0.486	0.294	0.165	0.063	-0.014	-0.014	-0.012	-0.018	-0.010	-0.011	-0.013	-0.009
Starting out	0.000	-22.972	-1.634	-1.183	1.037	3.965	0.558	0.768	-0.013	-0.011	-0.026	-0.018	-0.016	-0.024	-0.012	-0.015
Executive Wealth	0.000	-19.855	-22.066	-2.550	1.749	1.300	0.951	0.591	-0.029	-0.023	-0.040	-0.033	-0.032	-0.038	-0.040	-0.036
Not Private Households	0.000	-7.151	-3.997	-2.962	6.383	4.515	1.734	1.256	-0.037	-0.031	-0.036	-0.032	-0.043	-0.042	-0.038	-0.034
Steady Neighbourhoods	0.000	-4.020	-6.998	-4.397	2.979	2.029	0.650	0.474	-0.035	-0.049	-0.031	-0.046	-0.038	-0.037	-0.042	-0.022
Career Climbers	0.000	-1.169	-4.240	-3.173	2.112	4.430	0.500	0.561	-0.022	-0.022	-0.043	-0.025	-0.030	-0.024	-0.018	-0.020
Successful Suburbs	0.000	-2.029	-3.831	-1.663	-5.789	6.742	2.163	1.255	-0.028	-0.031	-0.031	-0.029	-0.021	-0.034	-0.035	-0.030
Modest Means	0.000	-28.306	-3.687	-1.291	0.577	0.578	0.903	0.495	-0.013	-0.010	-0.010	-0.019	-0.018	-0.009	-0.021	-0.016
Student life	0.000	-6.212	-3.752	-8.450	1.340	1.659	0.811	0.459	-0.030	-0.034	-0.028	-0.024	-0.036	-0.026	-0.028	-0.034
Striving Families	0.000	-2.733	-1.212	-271.240	1.151	3.245	0.538	0.320	-0.023	-0.028	-0.027	-0.020	-0.030	-0.026	-0.031	-0.023
Comfortable Seniors	0.000	-9.189	-103.510	-8.275	3.339	4.966	3.254	1.263	-0.053	-0.067	-0.069	-0.053	-0.042	-0.069	-0.044	-0.057
Countryside Communities	0.000	-11.916	-77.617	-7.230	2.078	0.690	0.877	0.516	-0.024	-0.032	-0.030	-0.020	-0.033	-0.025	-0.025	-0.031
Poorer Pensioners	0.000	-27.782	-16.834	-6.263	4.946	16.125	1.900	2.986	-0.034	-0.030	-0.035	-0.051	-0.053	-0.035	-0.061	-0.044
Young Hardship	0.000	-2.304	-0.977	-0.437	0.786	2.177	0.879	0.888	-0.007	-0.007	-0.008	-0.012	-0.005	-0.008	-0.005	-0.007
Difficult Circumstances	0.000	-46.826	-6.003	-10.733	-62.707	7.175	2.892	1.241	-0.069	-0.056	-0.045	-0.064	-0.070	-0.053	-0.051	-0.061
Struggling Estates	0.000	-6.063	-3.338	-2.499	2.837	5.539	3.519	2.325	-0.009	-0.022	-0.022	-0.015	-0.024	-0.027	-0.037	-0.014
Mean	0.000	-11.360	-14.927	-18.487	-1.919	3.738	1.562	0.894	-0.026	-0.027	-0.028	-0.028	-0.029	-0.028	-0.029	-0.026
Variance	0.000	12.395	27.601	61.408	14.932	3.683	1.429	0.732	0.016	0.016	0.015	0.015	0.016	0.016	0.015	0.016
Mean/Variance	0.000	-0.917	-0.541	-0.301	-0.129	1.015	1.093	1.221	-1.622	-1.715	-1.852	-1.808	-1.830	-1.789	-1.912	-1.676

Table H.2. Economic advantage E_A of using "Last Y Days" method to create a baseline for retailers and customers paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-5.785	-1.616	-5.149	1.113	0.536	0.486	1.149	-0.019	-0.018	-0.012	-0.015	-0.014	-0.012	-0.010	-0.022
City Sophisticates	0.000	-1.288	-8.620	-0.265	0.329	0.255	0.641	0.077	-0.003	-0.003	-0.008	-0.008	-0.013	-0.004	-0.013	-0.005
Mature Money	0.000	-2.388	-41.014	-3.385	0.713	-2.529	0.279	0.144	-0.013	-0.009	-0.009	-0.011	-0.016	-0.010	-0.012	-0.008
Starting out	0.000	-18.438	-0.667	-1.470	0.494	0.529	0.154	0.194	-0.013	-0.010	-0.019	-0.009	-0.007	-0.012	-0.010	-0.010
Executive Wealth	0.000	-19.073	-17.984	31.793	46.063	1.455	2.054	0.849	-0.019	-0.026	-0.028	-0.021	-0.027	-0.018	-0.023	-0.030
Not Private Households	0.000	-56.130	-10.341	-6.890	50.075	6.265	0.904	0.634	-0.048	-0.031	-0.042	-0.049	-0.048	-0.042	-0.040	-0.040
Steady Neighbourhoods	0.000	-3.228	-9.026	-9.290	0.761	0.760	0.598	0.683	-0.014	-0.027	-0.031	-0.028	-0.029	-0.028	-0.024	-0.027
Career Climbers	0.000	-3.558	-7.569	60.822	1.242	1.451	0.727	0.769	-0.016	-0.016	-0.015	-0.021	-0.018	-0.017	-0.016	-0.013
Successful Suburbs	0.000	-1.426	-3.506	-0.406	1.693	3.797	-5.229	1.484	-0.028	-0.040	-0.027	-0.024	-0.023	-0.026	-0.020	-0.023
Modest Means	0.000	-3.365	-3.132	-4.990	1.228	1.027	0.398	0.529	-0.018	-0.015	-0.013	-0.020	-0.019	-0.016	-0.015	-0.022
Student life	0.000	-4.302	-7.603	120.660	1.982	1.463	89.502	0.775	-0.015	-0.037	-0.030	-0.029	-0.023	-0.026	-0.031	-0.026
Striving Families	0.000	-15.454	-1.414	-19.008	1.299	0.826	0.461	0.154	-0.014	-0.018	-0.017	-0.022	-0.017	-0.020	-0.018	-0.017
Comfortable Seniors	0.000	-11.803	-12.727	-10.467	-4.893	4.311	-18.472	1.205	-0.054	-0.039	-0.048	-0.063	-0.056	-0.069	-0.047	-0.048
Countryside Communities	0.000	-5.887	-61.911	-2.745	1.960	2.648	2.523	1.687	-0.016	-0.032	-0.027	-0.022	-0.034	-0.015	-0.011	-0.029
Poorer Pensioners	0.000	-8.091	-48.049	-4.863	3.360	2.016	2.665	1.509	-0.059	-0.045	-0.047	-0.051	-0.053	-0.043	-0.057	-0.038
Young Hardship	0.000	-9.599	-0.467	-100.360	0.668	-1.656	0.481	0.219	-0.009	-0.009	-0.005	-0.007	-0.006	-0.009	-0.005	-0.008
Difficult Circumstances	0.000	-17.226	-43.938	-6.925	5.748	3.137	2.055	0.797	-0.063	-0.051	-0.047	-0.064	-0.058	-0.065	-0.055	-0.055
Struggling Estates	0.000	-9.095	-9.049	-12.717	3.108	4.054	1.100	1.967	-0.015	-0.038	-0.020	-0.018	-0.025	-0.021	-0.033	-0.021
Mean	0.000	-10.896	-16.035	1.353	6.497	1.686	4.518	0.824	-0.024	-0.026	-0.025	-0.027	-0.027	-0.025	-0.024	-0.025
Variance	0.000	12.389	18.407	40.974	14.844	2.067	21.132	0.557	0.018	0.014	0.014	0.017	0.016	0.018	0.016	0.014
Mean/Variance	0.000	-0.880	-0.871	0.033	0.438	0.816	0.214	1.478	-1.350	-1.901	-1.804	-1.542	-1.680	-1.409	-1.572	-1.810

Table H.3. Economic advantage E_A of using "Low X of Y Days" method to create a baseline for retailers and customers paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-2.714	-86.562	-2.807	-328.440	1.174	0.805	0.821	-0.026	-0.021	-0.016	-0.022	-0.022	-0.020	-0.022	-0.020
City Sophisticates	0.000	-0.832	-6.292	-0.241	0.198	0.058	0.082	0.055	-0.002	-0.005	-0.005	-0.007	-0.008	-0.001	-0.007	-0.003
Mature Money	0.000	-5.314	-7.233	-0.366	0.965	0.654	0.401	-0.744	-0.010	-0.011	-0.008	-0.010	-0.011	-0.010	-0.010	-0.009
Starting out	0.000	-0.715	-26.380	-0.865	1.359	0.914	-1.267	-6.695	-0.010	-0.009	-0.011	-0.015	-0.005	-0.008	-0.005	-0.008
Executive Wealth	0.000	-9.878	-15.852	-1.840	4.777	2.023	1.732	3.009	-0.028	-0.029	-0.026	-0.027	-0.023	-0.028	-0.031	-0.028
Not Private Households	0.000	-53.052	-12.928	-6.658	4.244	1.806	5.685	1.077	-0.038	-0.042	-0.029	-0.023	-0.041	-0.052	-0.042	-0.039
Steady Neighbourhoods	0.000	-47.160	-37.539	-4.316	5.638	0.982	1.093	0.402	-0.016	-0.020	-0.019	-0.022	-0.018	-0.019	-0.024	-0.020
Career Climbers	0.000	-2.239	-8.464	-0.452	1.202	0.866	0.833	0.767	-0.024	-0.024	-0.019	-0.027	-0.023	-0.031	-0.017	-0.020
Successful Suburbs	0.000	-5.523	-1.970	-21.737	1.122	-0.458	0.852	0.432	-0.033	-0.039	-0.019	-0.036	-0.027	-0.041	-0.037	-0.028
Modest Means	0.000	-1.316	-9.581	301.860	6.300	1.333	2.348	0.627	-0.010	-0.018	-0.017	-0.023	-0.020	-0.011	-0.013	-0.020
Student life	0.000	-4.167	-3.986	-0.999	1.610	0.792	0.432	0.183	-0.034	-0.022	-0.023	-0.013	-0.030	-0.019	-0.028	-0.032
Striving Families	0.000	-1.363	-25.573	-3.475	1.081	0.952	1.164	0.315	-0.015	-0.016	-0.015	-0.015	-0.010	-0.014	-0.018	-0.016
Comfortable Seniors	0.000	-6.190	-83.905	-3.737	5.823	7.754	2.035	0.611	-0.030	-0.040	-0.027	-0.026	-0.033	-0.042	-0.040	-0.037
Countryside Communities	0.000	-3.372	-3.446	-6.189	1.637	0.468	0.309	0.222	-0.021	-0.021	-0.022	-0.019	-0.023	-0.014	-0.021	-0.018
Poorer Pensioners	0.000	-13.289	-13.224	-10.331	2.439	1.569	0.918	0.579	-0.038	-0.043	-0.045	-0.063	-0.055	-0.045	-0.074	-0.042
Young Hardship	0.000	-12.310	-1.509	-2.065	1.484	0.683	0.441	0.106	-0.007	-0.008	-0.017	-0.022	-0.007	-0.010	-0.011	-0.007
Difficult Circumstances	0.000	-28.386	-12.369	-48.203	2.999	6.169	3.468	1.762	-0.054	-0.061	-0.059	-0.058	-0.054	-0.052	-0.054	-0.064
Struggling Estates	0.000	-18.714	-2.116	-2.556	-2.256	2.413	1.617	1.751	-0.012	-0.025	-0.012	-0.012	-0.014	-0.015	-0.017	-0.008
Mean	0.000	-12.030	-19.940	10.279	-15.990	1.675	1.275	0.293	-0.023	-0.025	-0.022	-0.024	-0.024	-0.024	-0.026	-0.023
Variance	0.000	15.199	24.916	71.598	75.811	1.998	1.454	1.873	0.013	0.014	0.013	0.015	0.014	0.016	0.017	0.015
Mean/Variance	0.000	-0.791	-0.800	0.144	-0.211	0.838	0.877	0.157	-1.708	-1.766	-1.735	-1.679	-1.635	-1.539	-1.521	-1.553

Table H.4. Economic advantage E_A of using "Mid X of Y Days" method to create a baseline for retailers and customers paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-34.168	-5.603	-4.532	0.710	0.531	0.225	-1.536	-0.017	-0.014	-0.012	-0.010	-0.018	-0.012	-0.015	-0.012
City Sophisticates	0.000	-0.527	-0.888	-1.951	0.153	0.063	0.031	0.016	-0.002	-0.002	-0.004	-0.004	-0.006	-0.002	-0.009	-0.004
Mature Money	0.000	-0.891	-5.258	30.258	0.966	0.402	-1.100	0.349	-0.021	-0.020	-0.013	-0.015	-0.017	-0.016	-0.017	-0.013
Starting out	0.000	-1.748	-5.931	-3.142	8.358	1.304	0.230	-0.860	-0.011	-0.013	-0.009	-0.015	-0.010	-0.009	-0.010	-0.010
Executive Wealth	0.000	-1.959	-6.504	-4.953	-4.258	1.909	1.816	1.192	-0.042	-0.030	-0.038	-0.032	-0.029	-0.035	-0.036	-0.039
Not Private Households	0.000	-15.724	-2.841	-7.106	3.263	1.131	0.563	0.357	-0.022	-0.030	-0.031	-0.030	-0.033	-0.021	-0.017	-0.029
Steady Neighbourhoods	0.000	-3.398	-8.227	-18.731	0.960	0.572	0.516	0.445	-0.021	-0.027	-0.024	-0.026	-0.020	-0.020	-0.017	-0.018
Career Climbers	0.000	-4.085	-41.410	204.990	1.022	1.247	0.621	0.275	-0.016	-0.020	-0.013	-0.019	-0.020	-0.012	-0.014	-0.013
Successful Suburbs	0.000	-1.175	-2.544	-8.168	-5.161	0.874	1.649	1.349	-0.023	-0.028	-0.018	-0.023	-0.016	-0.021	-0.028	-0.022
Modest Means	0.000	-3.092	-38.546	42.399	4.154	0.661	5.425	1.258	-0.009	-0.013	-0.017	-0.021	-0.022	-0.012	-0.018	-0.016
Student life	0.000	-2.341	-4.594	-449.700	0.881	0.347	0.185	0.191	-0.026	-0.022	-0.017	-0.019	-0.023	-0.021	-0.027	-0.019
Striving Families	0.000	-3.496	-25.380	-1.676	1.925	0.384	0.345	0.932	-0.019	-0.022	-0.015	-0.018	-0.018	-0.017	-0.024	-0.014
Comfortable Seniors	0.000	-7.049	-5.893	-2.653	-3.580	3.879	6.766	1.641	-0.039	-0.030	-0.033	-0.021	-0.037	-0.032	-0.036	-0.032
Countryside Communities	0.000	-4.060	-4.266	-1.092	-6.871	6.945	7.412	33.266	-0.031	-0.027	-0.018	-0.030	-0.021	-0.016	-0.016	-0.021
Poorer Pensioners	0.000	-9.695	-4.755	-24.981	2.648	-5.885	-16.439	1.761	-0.043	-0.029	-0.048	-0.042	-0.035	-0.027	-0.049	-0.030
Young Hardship	0.000	-2.212	-15.093	-7.541	0.474	0.438	0.206	0.190	-0.008	-0.003	-0.008	-0.007	-0.007	-0.003	-0.006	-0.006
Difficult Circumstances	0.000	-82.894	-610.350	-6.340	2.317	1.853	1.345	1.079	-0.048	-0.046	-0.030	-0.043	-0.048	-0.041	-0.045	-0.034
Struggling Estates	0.000	-12.397	-2.284	-3.194	0.877	0.960	0.198	0.129	-0.011	-0.018	-0.019	-0.015	-0.016	-0.024	-0.023	-0.011
Mean	0.000	-10.606	-43.909	-14.895	0.491	0.979	0.555	2.335	-0.023	-0.022	-0.020	-0.022	-0.022	-0.019	-0.023	-0.019
Variance	0.000	19.214	137.890	116.490	3.492	2.305	4.745	7.546	0.013	0.010	0.011	0.010	0.011	0.010	0.012	0.010
Mean/Variance	0.000	-0.552	-0.318	-0.128	0.141	0.425	0.117	0.309	-1.755	-2.141	-1.826	-2.071	-2.077	-1.874	-1.898	-1.950

Table H.5. Economic advantage E_A of using "High X of Y Days" method to create a baseline for retailers and customers paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-3.293	-3.251	36.204	1.676	0.702	0.350	0.323	-0.025	-0.033	-0.018	-0.023	-0.017	-0.016	-0.023	-0.025
City Sophisticates	0.000	-5.697	-0.705	-1.902	0.074	0.032	0.043	0.017	-0.001	-0.003	-0.005	-0.004	-0.010	-0.002	-0.008	-0.006
Mature Money	0.000	-2.427	-0.982	-3.206	0.686	0.314	0.500	0.156	-0.014	-0.011	-0.008	-0.006	-0.007	-0.007	-0.012	-0.007
Starting out	0.000	-0.601	-1.250	-2.296	10.973	3.373	0.919	0.731	-0.005	-0.011	-0.011	-0.007	-0.011	-0.010	-0.008	-0.010
Executive Wealth	0.000	-10.346	-1.322	-4.385	3.208	1.305	0.996	0.793	-0.022	-0.023	-0.017	-0.018	-0.020	-0.022	-0.023	-0.020
Not Private Households	0.000	-4.907	-8.688	-500.020	2.488	15.461	5.791	1.142	-0.052	-0.038	-0.036	-0.047	-0.054	-0.042	-0.045	-0.044
Steady Neighbourhoods	0.000	-2.865	-2.860	-3.314	2.709	-3.756	-8.244	2.405	-0.061	-0.053	-0.056	-0.041	-0.055	-0.049	-0.066	-0.042
Career Climbers	0.000	-7.190	-1.818	-5.456	0.820	0.881	0.603	0.339	-0.010	-0.014	-0.012	-0.013	-0.019	-0.020	-0.016	-0.015
Successful Suburbs	0.000	-4.402	-5.551	91.659	3.826	1.234	1.448	0.586	-0.051	-0.070	-0.058	-0.062	-0.061	-0.075	-0.042	-0.084
Modest Means	0.000	-2.044	-2.210	-2.605	10.332	1.396	0.821	0.610	-0.031	-0.019	-0.026	-0.032	-0.035	-0.036	-0.032	-0.024
Student life	0.000	-11.646	-3.773	32.220	0.680	0.387	0.263	0.052	-0.016	-0.022	-0.024	-0.021	-0.034	-0.027	-0.025	-0.026
Striving Families	0.000	-3.299	-1.669	-1.863	1.038	0.894	0.585	0.379	-0.026	-0.021	-0.009	-0.021	-0.014	-0.019	-0.014	-0.014
Comfortable Seniors	0.000	-3.525	-17.410	-32.617	2.378	1.444	0.832	-1.107	-0.031	-0.024	-0.033	-0.027	-0.044	-0.036	-0.026	-0.039
Countryside Communities	0.000	-7.147	-2.330	-1.206	3.043	-10.578	1.061	0.714	-0.022	-0.026	-0.014	-0.020	-0.024	-0.017	-0.022	-0.023
Poorer Pensioners	0.000	-12.473	-8.925	-216.410	3.629	1.667	1.616	3.538	-0.057	-0.042	-0.035	-0.036	-0.049	-0.046	-0.062	-0.042
Young Hardship	0.000	-8.285	-3.592	-3.567	0.813	-1.167	2.795	0.282	-0.008	-0.007	-0.012	-0.009	-0.010	-0.007	-0.007	-0.009
Difficult Circumstances	0.000	-28.867	-9.423	-30.366	-113.970	3.830	6.777	2.866	-0.076	-0.064	-0.060	-0.059	-0.065	-0.068	-0.059	-0.063
Struggling Estates	0.000	-3.985	-5.831	-3.059	2.325	-12.705	0.665	1.056	-0.010	-0.025	-0.016	-0.012	-0.010	-0.020	-0.034	-0.015
Mean	0.000	-6.833	-4.533	-36.233	-3.515	0.262	0.990	0.827	-0.029	-0.028	-0.025	-0.026	-0.030	-0.029	-0.029	-0.028
Variance	0.000	6.267	4.144	126.070	26.948	5.603	2.870	1.073	0.021	0.018	0.017	0.017	0.019	0.020	0.018	0.020
Mean/Variance	0.000	-1.090	-1.094	-0.287	-0.130	0.047	0.345	0.771	-1.356	-1.540	-1.448	-1.502	-1.550	-1.438	-1.591	-1.387

Table H.6. Economic advantage E_A of using "Exponential Moving Average" method to create a baseline for retailers and customers paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-8.054	-2.530	-2.011	25.037	1.595	1.530	0.545	-0.019	-0.024	-0.011	-0.014	-0.022	-0.016	-0.016	-0.015
City Sophisticates	0.000	-4.616	-13.034	2.047	0.091	-0.079	0.056	0.029	-0.002	-0.002	-0.004	-0.004	-0.008	-0.003	-0.008	-0.006
Mature Money	0.000	-2.603	-1.734	-2.821	0.521	0.451	0.525	0.183	-0.014	-0.011	-0.013	-0.015	-0.011	-0.013	-0.019	-0.015
Starting out	0.000	-1.504	-8.212	-2.246	0.314	0.125	0.110	0.091	-0.017	-0.013	-0.017	-0.012	-0.015	-0.015	-0.011	-0.014
Executive Wealth	0.000	-22.298	-157.270	67.031	3.975	5.782	2.170	-11.344	-0.057	-0.050	-0.044	-0.051	-0.043	-0.055	-0.055	-0.048
Not Private Households	0.000	-54.361	-11.522	-5.034	2.893	1.623	0.742	0.728	-0.050	-0.045	-0.040	-0.033	-0.052	-0.034	-0.048	-0.037
Steady Neighbourhoods	0.000	-9.900	-2.904	-13.249	-4.389	1.467	0.732	0.538	-0.019	-0.022	-0.026	-0.015	-0.029	-0.014	-0.024	-0.025
Career Climbers	0.000	-27.483	-2.066	-6.221	-11.850	21.504	1.289	1.502	-0.022	-0.022	-0.022	-0.030	-0.017	-0.027	-0.020	-0.018
Successful Suburbs	0.000	-3.940	-6.327	-2.113	1.009	1.581	0.980	0.380	-0.034	-0.048	-0.040	-0.044	-0.028	-0.048	-0.036	-0.064
Modest Means	0.000	-3.518	-6.242	-2.426	1.234	0.786	7.250	0.707	-0.014	-0.019	-0.019	-0.027	-0.023	-0.015	-0.016	-0.016
Student life	0.000	-6.332	-1.954	-2.115	3.146	-2.663	1.000	1.324	-0.045	-0.049	-0.039	-0.048	-0.047	-0.054	-0.027	-0.059
Striving Families	0.000	-1.549	-8.664	-1.612	1.814	0.933	1.208	0.454	-0.018	-0.025	-0.019	-0.022	-0.025	-0.017	-0.014	-0.013
Comfortable Seniors	0.000	-28.446	-9.537	-19.718	3.203	1.631	1.308	0.743	-0.063	-0.039	-0.055	-0.049	-0.042	-0.063	-0.048	-0.061
Countryside Communities	0.000	-3.786	-75.472	-3.063	2.067	0.318	0.172	0.303	-0.030	-0.039	-0.031	-0.025	-0.042	-0.025	-0.016	-0.033
Poorer Pensioners	0.000	-29.919	-10.835	-10.669	5.057	2.767	2.450	1.519	-0.060	-0.052	-0.038	-0.052	-0.053	-0.032	-0.060	-0.041
Young Hardship	0.000	-13.986	-7.507	-2.172	-6.477	0.825	0.465	0.252	-0.009	-0.005	-0.008	-0.008	-0.015	-0.006	-0.007	-0.013
Difficult Circumstances	0.000	-67.160	-17.010	-6.342	18.613	-158.150	8.300	3.709	-0.114	-0.111	-0.068	-0.088	-0.084	-0.107	-0.072	-0.092
Struggling Estates	0.000	-45.750	-3.384	-5.445	1.898	21.919	2.729	-9.718	-0.015	-0.042	-0.029	-0.014	-0.017	-0.024	-0.045	-0.020
Mean	0.000	-18.622	-19.234	-1.010	2.675	-5.421	1.834	-0.447	-0.033	-0.034	-0.029	-0.031	-0.032	-0.032	-0.030	-0.033
Variance	0.000	19.360	37.184	17.224	7.924	37.630	2.234	3.669	0.027	0.024	0.017	0.021	0.019	0.025	0.019	0.023
Mean/Variance	0.000	-0.962	-0.517	-0.059	0.338	-0.144	0.821	-0.122	-1.252	-1.412	-1.756	-1.478	-1.684	-1.260	-1.561	-1.432

Table H.7. Economic advantage E_A of using "Linear Regression" method to create a baseline for retailers and customers paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-3.392	-5.385	-8.873	0.964	0.408	0.126	0.128	-0.018	-0.016	-0.012	-0.015	-0.014	-0.013	-0.008	-0.019
City Sophisticates	0.000	-0.713	-2.885	-0.285	0.325	0.201	0.313	0.044	-0.002	-0.003	-0.003	-0.003	-0.006	-0.002	-0.010	-0.003
Mature Money	0.000	-26.409	-6.891	-1.324	-2.463	2.142	0.333	0.327	-0.014	-0.006	-0.013	-0.013	-0.012	-0.011	-0.013	-0.011
Starting out	0.000	-8.423	-1.691	-3.872	0.939	0.903	1.154	0.645	-0.015	-0.018	-0.020	-0.025	-0.019	-0.017	-0.014	-0.016
Executive Wealth	0.000	-4.540	-13.688	-3.904	9.065	3.592	1.307	0.779	-0.029	-0.037	-0.034	-0.036	-0.030	-0.033	-0.037	-0.024
Not Private Households	0.000	-42.470	-150.830	-2.692	3.161	1.294	1.662	1.298	-0.041	-0.045	-0.041	-0.041	-0.037	-0.034	-0.039	-0.031
Steady Neighbourhoods	0.000	-11.035	-2.249	-3.146	7.170	1.011	1.356	1.089	-0.040	-0.028	-0.031	-0.025	-0.029	-0.037	-0.044	-0.040
Career Climbers	0.000	-3.800	-4.833	-1.384	1.010	0.492	0.347	-11.403	-0.020	-0.015	-0.016	-0.010	-0.015	-0.020	-0.016	-0.016
Successful Suburbs	0.000	-4.069	-9.937	-9.004	1.173	1.594	0.556	1.459	-0.026	-0.027	-0.026	-0.029	-0.027	-0.031	-0.028	-0.035
Modest Means	0.000	-3.893	-0.968	286.150	0.651	0.406	0.334	0.246	-0.015	-0.014	-0.012	-0.014	-0.020	-0.017	-0.015	-0.018
Student life	0.000	-5.811	-3.920	-13.760	-50.250	0.830	77.345	0.298	-0.021	-0.022	-0.016	-0.021	-0.026	-0.023	-0.020	-0.030
Striving Families	0.000	-3.885	-2.818	-4.484	1.872	1.271	0.861	0.436	-0.018	-0.023	-0.019	-0.019	-0.024	-0.026	-0.023	-0.018
Comfortable Seniors	0.000	-12.052	-11.600	-3.486	3.499	2.459	1.470	1.420	-0.039	-0.037	-0.034	-0.037	-0.031	-0.042	-0.032	-0.032
Countryside Communities	0.000	-16.899	-2.576	-1.637	-17.775	1.259	0.558	2.015	-0.027	-0.039	-0.033	-0.028	-0.021	-0.030	-0.025	-0.016
Poorer Pensioners	0.000	-15.585	-10.413	-118.130	8.165	2.021	3.872	1.856	-0.064	-0.034	-0.042	-0.062	-0.064	-0.038	-0.070	-0.049
Young Hardship	0.000	-3.638	-0.694	-42.675	0.621	3.657	0.306	0.339	-0.005	-0.004	-0.007	-0.005	-0.005	-0.003	-0.004	-0.005
Difficult Circumstances	0.000	-18.668	-9.856	-17.866	7.589	4.523	1.825	1.434	-0.040	-0.081	-0.052	-0.043	-0.080	-0.053	-0.062	-0.058
Struggling Estates	0.000	-1.483	-4.063	-33.336	10.051	2.598	0.414	1.009	-0.015	-0.032	-0.015	-0.010	-0.014	-0.021	-0.040	-0.020
Mean	0.000	-10.376	-13.628	0.905	-0.791	1.703	5.230	0.190	-0.025	-0.027	-0.024	-0.024	-0.026	-0.025	-0.028	-0.024
Variance	0.000	10.332	33.497	74.353	13.387	1.214	17.512	2.873	0.015	0.018	0.013	0.015	0.018	0.013	0.018	0.014
Mean/Variance	0.000	-1.004	-0.407	0.012	-0.059	1.403	0.299	0.066	-1.696	-1.501	-1.811	-1.624	-1.439	-1.909	-1.552	-1.737

Table H.8. Economic advantage E_A of using "Polynomial Interpolation" method to create a baseline for retailers and customers paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-1.825	-2.199	188.950	0.709	0.404	0.351	0.398	-0.030	-0.027	-0.022	-0.020	-0.024	-0.028	-0.014	-0.034
City Sophisticates	0.000	-0.756	-0.534	-0.960	0.182	0.128	0.104	0.040	-0.002	-0.003	-0.003	-0.004	-0.004	-0.001	-0.006	-0.002
Mature Money	0.000	-6.217	-1.924	-8.419	0.703	-5.437	1.115	0.278	-0.017	-0.011	-0.008	-0.012	-0.011	-0.010	-0.008	-0.011
Starting out	0.000	-8.472	-1.109	-8.862	0.785	0.577	0.282	0.204	-0.011	-0.019	-0.013	-0.017	-0.019	-0.012	-0.008	-0.015
Executive Wealth	0.000	-14.693	-7.021	-9.491	2.833	1.236	1.554	0.760	-0.021	-0.023	-0.028	-0.016	-0.028	-0.021	-0.027	-0.027
Not Private Households	0.000	-8.488	-89.040	-10.747	1.550	1.232	0.581	0.421	-0.036	-0.035	-0.034	-0.029	-0.025	-0.031	-0.025	-0.033
Steady Neighbourhoods	0.000	-11.210	-5.155	-18.535	-1.998	2.545	1.993	0.527	-0.020	-0.018	-0.014	-0.020	-0.016	-0.019	-0.015	-0.015
Career Climbers	0.000	-25.316	-5.203	22.606	2.524	0.744	0.257	0.174	-0.019	-0.013	-0.018	-0.018	-0.013	-0.012	-0.018	-0.018
Successful Suburbs	0.000	-2.445	-35.987	-47.593	0.641	0.464	0.230	0.230	-0.016	-0.024	-0.015	-0.030	-0.017	-0.034	-0.013	-0.017
Modest Means	0.000	-9.564	-41.058	-4.524	3.461	1.246	5.223	0.604	-0.013	-0.019	-0.017	-0.027	-0.020	-0.021	-0.022	-0.027
Student life	0.000	-13.777	-3.044	-2.230	0.725	2.900	0.706	0.562	-0.016	-0.031	-0.021	-0.018	-0.026	-0.020	-0.025	-0.025
Striving Families	0.000	-5.218	-42.622	-0.783	0.976	-0.824	2.556	0.418	-0.015	-0.019	-0.017	-0.017	-0.018	-0.013	-0.021	-0.010
Comfortable Seniors	0.000	-50.004	-6.653	-6.773	3.181	2.117	1.370	0.715	-0.036	-0.044	-0.041	-0.038	-0.030	-0.056	-0.032	-0.024
Countryside Communities	0.000	-5.562	-10.980	-2.918	3.587	-1.012	0.903	1.082	-0.032	-0.034	-0.033	-0.027	-0.023	-0.009	-0.018	-0.018
Poorer Pensioners	0.000	-18.761	-5.536	-13.690	3.869	4.168	-4.017	2.494	-0.038	-0.047	-0.054	-0.060	-0.069	-0.045	-0.058	-0.043
Young Hardship	0.000	-8.259	-0.994	-5.595	0.443	0.633	0.255	0.227	-0.003	-0.004	-0.005	-0.006	-0.005	-0.007	-0.004	-0.005
Difficult Circumstances	0.000	-15.403	-17.992	-57.853	-61.253	12.991	5.359	6.113	-0.067	-0.044	-0.050	-0.058	-0.074	-0.054	-0.065	-0.053
Struggling Estates	0.000	-3.629	-7.400	-3.169	3.170	-5.499	3.637	-49.862	-0.022	-0.039	-0.019	-0.012	-0.014	-0.031	-0.026	-0.034
Mean	0.000	-11.644	-15.803	0.523	-1.884	1.034	1.248	-1.923	-0.023	-0.025	-0.023	-0.024	-0.024	-0.024	-0.022	-0.023
Variance	0.000	11.167	22.271	48.779	14.477	3.757	2.047	11.708	0.015	0.013	0.014	0.015	0.018	0.015	0.016	0.013
Mean/Variance	0.000	-1.043	-0.710	0.011	-0.130	0.275	0.610	-0.164	-1.547	-1.937	-1.640	-1.589	-1.333	-1.545	-1.421	-1.775

Table H.9. Economic advantage E_A of using "Neural Network" method to create a baseline for retailers and customers paying a Flat-rate tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-40.863	-0.357	-1.928	0.617	0.179	0.140	0.345	-0.017	-0.021	-0.019	-0.022	-0.019	-0.025	-0.019	-0.019
City Sophisticates	0.000	-0.404	-0.618	-0.746	-2.192	0.262	0.139	0.162	-0.003	-0.005	-0.006	-0.007	-0.009	-0.004	-0.009	-0.004
Mature Money	0.000	-9.636	-6.228	-4.744	0.486	0.419	1.226	0.208	-0.009	-0.008	-0.007	-0.011	-0.011	-0.007	-0.014	-0.009
Starting out	0.000	-4.745	175.400	7.046	0.134	0.083	0.156	0.048	-0.020	-0.014	-0.013	-0.029	-0.017	-0.025	-0.022	-0.033
Executive Wealth	0.000	-7.827	-30.905	-7.513	2.710	1.884	-1.242	-3.248	-0.023	-0.022	-0.028	-0.026	-0.028	-0.031	-0.030	-0.037
Not Private Households	0.000	-6.673	-6.489	-5.598	-6.553	6.684	4.507	6.741	-0.052	-0.047	-0.042	-0.040	-0.038	-0.057	-0.025	-0.028
Steady Neighbourhoods	0.000	-7.865	-1.700	-2.316	2.258	2.327	1.354	1.884	-0.017	-0.017	-0.018	-0.019	-0.024	-0.019	-0.018	-0.014
Career Climbers	0.000	-7.193	-1.449	-4.790	1.177	9.676	0.631	2.049	-0.021	-0.012	-0.018	-0.021	-0.022	-0.020	-0.022	-0.025
Successful Suburbs	0.000	-30.000	-1.811	7.497	0.504	0.179	0.134	0.091	-0.020	-0.021	-0.025	-0.023	-0.025	-0.044	-0.022	-0.044
Modest Means	0.000	-15.271	-4.184	-9.695	0.966	0.457	0.933	0.360	-0.013	-0.015	-0.008	-0.018	-0.017	-0.012	-0.017	-0.021
Student life	0.000	-1.630	-5.755	-7.941	2.185	1.230	0.597	0.285	-0.027	-0.027	-0.021	-0.025	-0.027	-0.019	-0.025	-0.032
Striving Families	0.000	-1.193	-1.255	-3.118	-34.671	-1.771	1.672	1.646	-0.021	-0.017	-0.018	-0.017	-0.020	-0.019	-0.021	-0.025
Comfortable Seniors	0.000	-6.425	-11.887	-5.543	11.346	6.031	-2.648	1.613	-0.033	-0.037	-0.031	-0.027	-0.026	-0.041	-0.034	-0.033
Countryside Communities	0.000	-20.719	-1.548	61.971	1.210	0.387	0.288	0.133	-0.030	-0.024	-0.021	-0.029	-0.021	-0.017	-0.016	-0.015
Poorer Pensioners	0.000	-5.517	-8.339	-3.471	4.238	2.278	0.987	0.905	-0.058	-0.054	-0.058	-0.045	-0.058	-0.051	-0.064	-0.039
Young Hardship	0.000	-1.399	-3.008	-0.698	3.095	2.779	0.521	0.221	-0.007	-0.004	-0.003	-0.005	-0.013	-0.008	-0.003	-0.004
Difficult Circumstances	0.000	-16.643	-27.158	-3.821	10.860	18.469	-274.550	2.408	-0.065	-0.058	-0.052	-0.051	-0.060	-0.052	-0.050	-0.053
Struggling Estates	0.000	-8.748	-5.091	-22.969	1.657	1.977	0.781	3.377	-0.017	-0.031	-0.029	-0.019	-0.024	-0.019	-0.032	-0.017
Mean	0.000	-10.708	3.201	-0.465	0.001	2.974	-14.687	1.068	-0.025	-0.024	-0.023	-0.024	-0.026	-0.026	-0.025	-0.025
Variance	0.000	10.367	42.598	16.394	9.276	4.641	63.040	1.929	0.017	0.015	0.015	0.012	0.014	0.016	0.014	0.013
Mean/Variance	0.000	-1.033	0.075	-0.028	0.000	0.641	-0.233	0.554	-1.498	-1.573	-1.567	-2.054	-1.877	-1.640	-1.773	-1.894

Table H.10. Economic advantage E_A of using “Historical Data” method to create a baseline for retailers and customers paying a Time-Of-Use tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-0.430	-0.130	9.319	0.523	0.264	-0.668	0.067	0.002	0.002	0.002	0.001	0.002	0.001	0.001	0.002
City Sophisticates	0.000	-0.341	-0.844	-0.229	0.051	0.027	0.024	0.021	0.003	0.002	0.002	0.001	0.005	0.004	0.002	0.002
Mature Money	0.000	-27.833	-2.185	-0.755	0.278	0.771	0.341	0.186	0.008	0.005	0.003	0.011	0.006	0.007	0.003	0.007
Starting out	0.000	-1.268	-1.853	-6.891	0.313	0.235	0.178	0.106	0.009	0.010	0.010	0.019	0.028	0.017	0.019	0.013
Executive Wealth	0.000	-3.193	-9.617	-4.926	0.233	0.242	0.137	0.281	0.017	0.019	0.014	0.013	0.011	0.014	0.020	0.016
Not Private Households	0.000	-9.027	-71.947	37.599	0.455	0.183	0.140	0.119	0.016	0.020	0.014	0.014	0.015	0.027	0.019	0.026
Steady Neighbourhoods	0.000	-5.530	-1.262	-1.461	-1.601	0.321	0.189	0.139	0.007	0.009	0.006	0.009	0.012	0.015	0.009	0.011
Career Climbers	0.000	-12.704	-1.489	118.940	0.726	2.043	0.303	0.481	0.025	0.035	0.022	0.029	0.036	0.027	0.032	0.030
Successful Suburbs	0.000	-1.652	-1.094	-1.261	0.658	0.555	0.512	0.207	0.006	0.012	0.006	0.010	0.007	0.004	0.008	0.012
Modest Means	0.000	-2.215	-0.424	-3.701	0.188	0.355	0.079	-0.060	0.003	0.004	0.008	0.003	0.008	0.006	0.004	0.007
Student life	0.000	-12.324	-0.611	-0.768	0.611	0.306	0.261	0.269	0.008	0.014	0.006	0.011	0.005	0.010	0.008	0.007
Striving Families	0.000	-1.785	-1.167	-1.944	-2.120	1.530	0.674	0.370	0.020	0.010	0.034	0.012	0.014	0.011	0.012	0.013
Comfortable Seniors	0.000	-1.302	-2.033	-0.638	1.019	0.240	0.271	0.251	0.008	0.009	0.007	0.007	0.007	0.008	0.005	0.008
Countryside Communities	0.000	-10.632	-2.296	-5.994	0.283	0.327	0.288	0.153	0.015	0.011	0.013	0.014	0.013	0.010	0.012	0.015
Poorer Pensioners	0.000	-1.929	-4.709	-10.111	-7.367	0.308	0.168	0.050	0.005	0.006	0.007	0.008	0.010	0.008	0.004	0.007
Young Hardship	0.000	-30.952	-22.349	-43.714	28.242	15.800	5.636	4.130	0.038	0.019	0.029	0.019	0.023	0.016	0.026	0.031
Difficult Circumstances	0.000	-3.649	-25.737	-10.511	8.394	-25.022	2.410	-0.765	0.029	0.047	0.034	0.060	0.037	0.038	0.039	0.039
Struggling Estates	0.000	-1.479	-0.476	4.523	0.120	0.075	0.018	0.014	0.011	0.004	0.005	0.015	0.008	0.006	0.004	0.014
Mean	0.000	-7.125	-8.346	4.305	1.723	-0.080	0.609	0.334	0.013	0.013	0.012	0.014	0.014	0.013	0.013	0.014
Variance	0.000	8.823	17.037	31.260	6.989	7.007	1.346	0.953	0.010	0.011	0.010	0.013	0.010	0.009	0.011	0.010
Mean/Variance	0.000	-0.808	-0.490	0.138	0.246	-0.011	0.452	0.351	1.308	1.163	1.212	1.104	1.345	1.375	1.188	1.405

Table H.11. Economic advantage E_A of using “Last Y Days” method to create a baseline for retailers and customers paying a Time-Of-Use tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-0.553	-0.204	7.124	0.143	0.632	0.075	0.070	0.004	0.002	0.004	0.002	0.002	0.003	0.002	0.003
City Sophisticates	0.000	-0.309	-0.107	-0.396	2.064	0.057	0.036	0.034	0.002	0.001	0.002	0.002	0.005	0.004	0.002	0.001
Mature Money	0.000	-1.753	-4.206	-1.527	0.734	0.928	0.634	0.271	0.007	0.005	0.005	0.008	0.005	0.008	0.005	0.007
Starting out	0.000	-0.534	-1.407	-6.687	3.712	-51.801	0.455	1.076	0.012	0.012	0.008	0.013	0.010	0.009	0.011	0.013
Executive Wealth	0.000	-2.646	-9.803	-0.733	0.816	-1.644	9.814	0.387	0.009	0.011	0.012	0.008	0.012	0.015	0.011	0.011
Not Private Households	0.000	-3.725	-3.967	-71.242	0.397	1.333	0.393	0.339	0.035	0.030	0.026	0.020	0.013	0.018	0.017	0.044
Steady Neighbourhoods	0.000	-8.084	-6.884	-0.661	1.060	0.186	0.257	0.217	0.009	0.010	0.006	0.006	0.021	0.018	0.010	0.013
Career Climbers	0.000	-5.662	-4.932	-6.020	1.317	0.441	0.212	0.233	0.023	0.028	0.016	0.026	0.016	0.012	0.022	0.026
Successful Suburbs	0.000	-2.762	-3.296	10.093	0.668	0.215	0.081	0.073	0.005	0.010	0.005	0.009	0.008	0.005	0.012	0.014
Modest Means	0.000	-2.646	-0.252	-0.536	0.921	0.627	0.264	0.114	0.003	0.002	0.005	0.004	0.007	0.008	0.005	0.006
Student life	0.000	-0.903	-3.423	-2.615	0.952	0.406	0.233	0.169	0.007	0.006	0.004	0.013	0.008	0.006	0.011	0.005
Striving Families	0.000	-6.915	-0.927	-1.378	0.629	-0.958	1.210	0.786	0.008	0.007	0.015	0.008	0.007	0.013	0.015	0.011
Comfortable Seniors	0.000	-0.743	-1.015	-3.326	0.392	0.072	0.095	0.228	0.007	0.006	0.005	0.005	0.012	0.006	0.007	0.008
Countryside Communities	0.000	-1.370	-1.566	-1.519	1.588	1.287	0.923	0.705	0.010	0.013	0.011	0.011	0.011	0.014	0.012	0.013
Poorer Pensioners	0.000	-9.613	-2.757	25.545	2.604	15.284	0.488	0.313	0.005	0.009	0.008	0.004	0.008	0.010	0.005	0.006
Young Hardship	0.000	-116.240	-26.034	-5.502	12.677	-14.279	4.514	3.538	0.031	0.011	0.012	0.021	0.012	0.016	0.021	0.025
Difficult Circumstances	0.000	-44.040	-5.254	-2.291	5.911	1.514	1.057	2.041	0.043	0.039	0.032	0.030	0.045	0.041	0.044	0.031
Struggling Estates	0.000	-1.339	-0.530	-0.556	0.703	0.605	0.076	0.081	0.008	0.005	0.006	0.007	0.006	0.006	0.004	0.012
Mean	0.000	-11.657	-4.254	-3.457	2.071	-2.505	1.157	0.593	0.013	0.012	0.010	0.011	0.012	0.012	0.012	0.014
Variance	0.000	27.169	5.859	17.963	2.918	12.952	2.325	0.859	0.012	0.010	0.008	0.008	0.009	0.008	0.010	0.011
Mean/Variance	0.000	-0.429	-0.726	-0.192	0.710	-0.193	0.497	0.691	1.086	1.170	1.306	1.404	1.247	1.394	1.236	1.282

Table H.12. Economic advantage E_A of using "Low X of Y Days" method to create a baseline for retailers and customers paying a Time-Of-Use tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-0.544	-0.092	17.140	0.256	0.065	0.035	0.065	0.002	0.004	0.003	0.002	0.004	0.003	0.002	0.004
City Sophisticates	0.000	-3.852	-0.158	-0.095	-0.138	0.027	0.042	0.020	0.002	0.001	0.002	0.002	0.003	0.003	0.002	0.002
Mature Money	0.000	-15.874	-2.676	-2.182	0.711	0.398	0.315	0.379	0.004	0.006	0.003	0.006	0.005	0.004	0.004	0.007
Starting out	0.000	-2.479	-1.526	-5.376	0.406	0.263	0.192	0.124	0.014	0.010	0.009	0.017	0.024	0.012	0.011	0.014
Executive Wealth	0.000	-6.254	-43.286	-7.550	0.508	0.426	0.951	0.288	0.020	0.015	0.011	0.009	0.013	0.011	0.013	0.015
Not Private Households	0.000	-8.197	-5.263	-1.162	0.714	1.313	0.411	0.300	0.015	0.019	0.014	0.027	0.012	0.018	0.025	0.026
Steady Neighbourhoods	0.000	-1.890	-0.774	-1.528	0.463	0.422	8.000	0.201	0.018	0.012	0.009	0.010	0.013	0.020	0.013	0.020
Career Climbers	0.000	-6.309	-3.995	-1.008	0.470	0.187	0.164	0.087	0.026	0.019	0.021	0.017	0.020	0.017	0.014	0.021
Successful Suburbs	0.000	-1.776	-0.983	-3.503	0.270	0.350	0.180	0.222	0.005	0.006	0.005	0.007	0.004	0.003	0.004	0.011
Modest Means	0.000	-2.327	-0.506	-1.073	1.933	0.138	0.219	0.092	0.003	0.003	0.006	0.003	0.007	0.008	0.003	0.004
Student life	0.000	-0.682	-0.822	-5.156	1.067	0.810	0.528	0.466	0.004	0.007	0.006	0.007	0.005	0.006	0.004	0.003
Striving Families	0.000	-1.574	-0.713	73.263	0.394	0.199	-0.172	0.143	0.014	0.011	0.020	0.005	0.008	0.011	0.011	0.005
Comfortable Seniors	0.000	-1.057	-2.807	-1.052	0.489	0.462	0.612	1.828	0.006	0.006	0.005	0.004	0.012	0.004	0.003	0.007
Countryside Communities	0.000	-4.985	-0.775	-1.132	0.813	0.871	0.970	0.585	0.010	0.010	0.011	0.013	0.011	0.007	0.008	0.014
Poorer Pensioners	0.000	-1.959	-1.286	7.131	0.275	0.167	2.637	0.080	0.003	0.006	0.006	0.004	0.004	0.009	0.003	0.005
Young Hardship	0.000	-20.782	-22.759	-19.512	-24.965	2.416	0.933	0.664	0.019	0.010	0.012	0.016	0.018	0.008	0.024	0.017
Difficult Circumstances	0.000	-23.564	-8.949	-48.647	4.085	3.185	0.502	0.264	0.029	0.034	0.017	0.051	0.020	0.037	0.044	0.031
Struggling Estates	0.000	-1.249	-2.576	-1.331	0.494	2.049	0.201	-0.698	0.010	0.008	0.004	0.008	0.010	0.006	0.006	0.010
Mean	0.000	-5.853	-5.553	-0.154	-0.653	0.764	0.929	0.284	0.011	0.010	0.009	0.011	0.011	0.010	0.011	0.012
Variance	0.000	6.816	10.514	21.856	5.965	0.878	1.819	0.467	0.008	0.007	0.006	0.011	0.006	0.008	0.011	0.008
Mean/Variance	0.000	-0.859	-0.528	-0.007	-0.109	0.870	0.511	0.609	1.372	1.388	1.615	1.004	1.712	1.274	1.015	1.446

Table H.13. Economic advantage E_A of using "Mid X of Y Days" method to create a baseline for retailers and customers paying a Time-Of-Use tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-3.602	-1.480	1.437	0.092	0.059	0.020	0.024	0.004	0.003	0.004	0.001	0.003	0.004	0.003	0.003
City Sophisticates	0.000	-2.867	-0.412	-0.516	-1.143	0.043	0.082	0.093	0.002	0.002	0.003	0.002	0.002	0.003	0.002	0.002
Mature Money	0.000	-9.255	75.268	7.051	0.247	0.224	0.058	0.031	0.004	0.004	0.003	0.008	0.007	0.007	0.005	0.007
Starting out	0.000	-0.384	-2.689	-4.621	0.673	0.121	0.233	0.200	0.011	0.010	0.008	0.008	0.012	0.011	0.012	0.010
Executive Wealth	0.000	-3.296	-1.705	-3.730	0.756	0.397	-3.264	0.349	0.012	0.009	0.010	0.009	0.011	0.010	0.009	0.012
Not Private Households	0.000	-2.198	-3.124	-2.065	0.772	0.454	0.221	0.100	0.019	0.014	0.022	0.014	0.016	0.017	0.011	0.017
Steady Neighbourhoods	0.000	-1.373	-0.543	-1.155	0.496	0.399	0.138	0.472	0.012	0.010	0.005	0.009	0.011	0.014	0.010	0.013
Career Climbers	0.000	-1.411	-1.152	-1.147	-1.301	3.947	-16.682	0.393	0.019	0.022	0.015	0.019	0.019	0.021	0.023	0.026
Successful Suburbs	0.000	-4.954	-1.131	-0.825	1.542	1.009	0.382	0.307	0.003	0.010	0.004	0.005	0.005	0.003	0.004	0.009
Modest Means	0.000	-0.790	-0.477	-479.020	16.595	0.294	0.139	0.054	0.004	0.002	0.005	0.002	0.006	0.004	0.002	0.004
Student life	0.000	-8.965	-3.132	-0.832	0.463	-4.016	0.236	0.193	0.007	0.009	0.005	0.013	0.005	0.005	0.009	0.005
Striving Families	0.000	-1.070	-0.949	-0.860	1.939	0.926	0.432	0.204	0.015	0.007	0.017	0.007	0.007	0.012	0.009	0.013
Comfortable Seniors	0.000	-0.655	-1.438	-1.160	0.748	0.108	0.131	0.271	0.009	0.006	0.006	0.005	0.005	0.005	0.004	0.006
Countryside Communities	0.000	-14.839	-1.120	12.997	0.334	0.235	0.078	0.083	0.007	0.007	0.008	0.011	0.018	0.005	0.014	0.013
Poorer Pensioners	0.000	-2.391	-22.797	-3.252	0.397	0.500	0.376	0.068	0.005	0.005	0.007	0.006	0.006	0.007	0.004	0.005
Young Hardship	0.000	-52.551	-27.606	-10.608	23.174	12.839	4.478	3.737	0.023	0.011	0.011	0.015	0.013	0.010	0.013	0.028
Difficult Circumstances	0.000	-10.150	-39.880	-3.481	3.422	1.746	0.936	0.475	0.026	0.043	0.024	0.039	0.053	0.030	0.025	0.032
Struggling Estates	0.000	-1.111	-0.556	-7.191	0.715	0.374	0.067	0.052	0.007	0.004	0.006	0.005	0.005	0.003	0.005	0.008
Mean	0.000	-6.770	-1.940	-27.721	2.773	1.092	-0.663	0.395	0.011	0.010	0.009	0.010	0.011	0.009	0.009	0.012
Variance	0.000	11.786	21.743	109.570	6.229	3.172	4.101	0.823	0.007	0.009	0.006	0.008	0.011	0.007	0.007	0.009
Mean/Variance	0.000	-0.574	-0.089	-0.253	0.445	0.344	-0.162	0.480	1.485	1.054	1.461	1.171	1.013	1.341	1.394	1.374

Table H.14. Economic advantage E_A of using "High X of Y Days" method to create a baseline for retailers and customers paying a Time-Of-Use tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-0.550	-0.803	-0.093	-0.207	0.108	0.106	0.096	0.002	0.004	0.004	0.002	0.003	0.002	0.003	0.003
City Sophisticates	0.000	-4.572	0.654	0.294	0.010	0.003	0.003	0.004	0.003	0.002	0.002	0.002	0.006	0.007	0.003	0.003
Mature Money	0.000	-1.973	-8.940	-1.082	2.278	0.590	1.578	0.351	0.009	0.005	0.006	0.012	0.008	0.008	0.008	0.007
Starting out	0.000	-2.748	-0.513	-2.334	0.416	0.410	0.168	0.102	0.013	0.011	0.010	0.009	0.017	0.022	0.013	0.026
Executive Wealth	0.000	-3.287	-1.752	-3.681	1.189	0.415	0.377	0.331	0.012	0.014	0.013	0.009	0.009	0.010	0.011	0.009
Not Private Households	0.000	-5.644	-5.568	-3.511	0.769	0.347	0.571	1.728	0.030	0.038	0.028	0.034	0.023	0.032	0.037	0.028
Steady Neighbourhoods	0.000	-3.198	-1.508	84.586	0.395	0.499	0.705	0.783	0.014	0.008	0.008	0.009	0.011	0.011	0.013	0.014
Career Climbers	0.000	-1.120	-15.786	-1.343	0.599	0.559	0.463	-3.794	0.012	0.026	0.018	0.019	0.020	0.024	0.011	0.027
Successful Suburbs	0.000	-0.628	-1.292	-92.465	7.941	22.215	-0.408	1.054	0.004	0.010	0.006	0.007	0.004	0.002	0.005	0.010
Modest Means	0.000	-1.641	-0.701	-1.177	1.280	0.486	0.309	0.068	0.003	0.003	0.005	0.003	0.006	0.009	0.005	0.008
Student life	0.000	-1.781	-0.826	-6.864	0.575	0.236	0.462	0.202	0.007	0.007	0.004	0.009	0.004	0.006	0.013	0.007
Striving Families	0.000	-1.643	-2.675	-4.341	1.032	0.459	0.515	0.199	0.011	0.009	0.027	0.010	0.013	0.011	0.010	0.012
Comfortable Seniors	0.000	-1.546	-0.691	-8.949	0.216	0.091	0.062	0.094	0.009	0.006	0.007	0.004	0.008	0.008	0.003	0.012
Countryside Communities	0.000	-21.204	-2.312	-1.107	0.371	0.300	0.242	0.136	0.007	0.014	0.006	0.008	0.009	0.009	0.011	0.014
Poorer Pensioners	0.000	-1.131	-1.456	-1.205	0.401	0.180	0.724	0.100	0.003	0.008	0.007	0.005	0.008	0.006	0.005	0.005
Young Hardship	0.000	-44.506	-77.997	-70.681	4.539	5.774	2.639	2.639	0.032	0.012	0.020	0.020	0.011	0.015	0.024	0.027
Difficult Circumstances	0.000	-9.402	-5.105	-22.451	10.560	2.216	11.687	2.832	0.030	0.032	0.027	0.045	0.031	0.021	0.044	0.033
Struggling Estates	0.000	-3.357	-0.637	-0.911	1.012	0.537	0.202	0.504	0.025	0.006	0.011	0.011	0.015	0.008	0.005	0.018
Mean	0.000	-6.107	-7.106	-7.629	1.854	1.968	1.134	0.413	0.013	0.012	0.012	0.012	0.011	0.012	0.012	0.015
Variance	0.000	10.430	17.616	33.617	2.844	5.079	2.640	1.326	0.010	0.010	0.008	0.011	0.007	0.008	0.011	0.009
Mean/Variance	0.000	-0.586	-0.403	-0.227	0.652	0.387	0.429	0.311	1.285	1.217	1.398	1.087	1.573	1.498	1.103	1.578

Table H.15. Economic advantage E_A of using “Exponential Moving Average” method to create a baseline for retailers and customers paying a Time-Of-Use tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-0.337	-1.069	-0.361	0.203	0.101	0.092	0.085	0.002	0.002	0.003	0.002	0.003	0.002	0.003	0.003
City Sophisticates	0.000	-0.416	-0.095	-0.572	0.156	0.048	0.445	0.034	0.002	0.001	0.003	0.001	0.004	0.004	0.002	0.002
Mature Money	0.000	-6.207	-6.024	16.098	-3.846	0.215	0.559	0.209	0.006	0.004	0.005	0.007	0.007	0.007	0.007	0.005
Starting out	0.000	-0.952	-11.652	-5.335	0.510	0.180	0.211	0.168	0.007	0.010	0.007	0.011	0.016	0.019	0.010	0.013
Executive Wealth	0.000	-2.725	-1.755	-1.950	0.689	2.268	1.136	0.587	0.017	0.018	0.026	0.015	0.022	0.022	0.019	0.020
Not Private Households	0.000	-14.651	-3.249	-2.639	1.155	1.991	20.342	1.342	0.036	0.029	0.027	0.052	0.024	0.046	0.025	0.025
Steady Neighbourhoods	0.000	-1.842	-0.934	-1.156	0.541	0.267	0.318	0.379	0.007	0.008	0.005	0.008	0.010	0.006	0.006	0.014
Career Climbers	0.000	-2.372	-13.071	72.339	9.664	0.900	0.989	0.415	0.028	0.050	0.027	0.042	0.049	0.049	0.034	0.061
Successful Suburbs	0.000	-2.380	-0.817	-0.989	1.348	0.572	2.310	0.684	0.005	0.013	0.013	0.010	0.009	0.006	0.008	0.026
Modest Means	0.000	-0.948	-0.357	-6.003	1.275	0.478	0.238	0.212	0.006	0.004	0.014	0.005	0.010	0.009	0.003	0.006
Student life	0.000	-1.579	-1.233	-1.934	1.922	0.737	0.353	0.512	0.009	0.014	0.005	0.009	0.008	0.009	0.011	0.009
Striving Families	0.000	-1.685	-1.413	-78.175	9.736	1.611	-4.903	0.798	0.023	0.010	0.033	0.016	0.018	0.013	0.016	0.025
Comfortable Seniors	0.000	-2.679	-0.552	25.798	0.800	0.386	0.343	0.243	0.019	0.008	0.011	0.007	0.010	0.007	0.004	0.010
Countryside Communities	0.000	-10.707	-70.893	-0.973	0.694	0.640	0.211	0.152	0.012	0.012	0.014	0.013	0.012	0.015	0.014	0.016
Poorer Pensioners	0.000	-1.283	-4.648	-7.520	-1.782	0.839	0.686	0.187	0.007	0.012	0.013	0.011	0.014	0.014	0.008	0.013
Young Hardship	0.000	-157.370	-32.727	-92.532	25.913	18.194	3.214	1.875	0.060	0.044	0.035	0.057	0.055	0.052	0.055	0.062
Difficult Circumstances	0.000	-19.782	-14.704	-28.732	5.003	2.796	4.404	1.299	0.044	0.044	0.045	0.083	0.065	0.071	0.045	0.055
Struggling Estates	0.000	-0.921	-1.000	-4.490	0.613	0.275	0.128	0.133	0.014	0.010	0.011	0.013	0.012	0.006	0.005	0.010
Mean	0.000	-12.713	-9.233	-6.618	3.033	1.805	1.726	0.517	0.017	0.016	0.016	0.020	0.019	0.020	0.015	0.021
Variance	0.000	35.477	16.938	34.179	6.447	4.050	4.848	0.498	0.016	0.015	0.012	0.022	0.018	0.020	0.015	0.019
Mean/Variance	0.000	-0.358	-0.545	-0.194	0.470	0.446	0.356	1.038	1.091	1.110	1.348	0.911	1.101	1.005	1.036	1.112

Table H.16. Economic advantage E_A of using "Linear Regression" method to create a baseline for retailers and customers paying a Time-Of-Use tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-2.843	-0.449	-0.385	0.087	0.186	0.023	0.013	0.002	0.002	0.003	0.002	0.003	0.002	0.003	0.003
City Sophisticates	0.000	-0.753	-0.166	-1.349	0.099	0.039	0.023	0.013	0.001	0.001	0.001	0.001	0.002	0.003	0.001	0.001
Mature Money	0.000	-14.264	-3.043	-6.524	1.211	1.217	-2.253	0.207	0.009	0.003	0.004	0.010	0.004	0.006	0.006	0.009
Starting out	0.000	-1.872	-2.144	-10.187	0.402	0.240	0.243	0.257	0.011	0.012	0.008	0.012	0.015	0.011	0.009	0.017
Executive Wealth	0.000	-2.683	-2.521	-2.011	0.773	1.481	1.064	-4.687	0.013	0.011	0.013	0.010	0.024	0.016	0.011	0.012
Not Private Households	0.000	-4.634	-4.126	85.783	2.786	-113.940	-28.667	0.586	0.021	0.030	0.016	0.020	0.019	0.026	0.013	0.022
Steady Neighbourhoods	0.000	-0.944	-4.942	-2.097	0.228	0.148	0.162	0.062	0.016	0.010	0.006	0.010	0.018	0.011	0.010	0.017
Career Climbers	0.000	-2.759	-2.865	-1.973	-4.595	0.426	0.365	0.226	0.032	0.033	0.028	0.017	0.014	0.022	0.024	0.035
Successful Suburbs	0.000	-1.451	-4.105	-3.443	0.475	1.449	0.256	0.157	0.005	0.011	0.008	0.012	0.009	0.006	0.006	0.011
Modest Means	0.000	-0.559	-2.350	-0.374	0.595	0.126	0.469	0.053	0.002	0.003	0.008	0.003	0.007	0.006	0.004	0.006
Student life	0.000	-10.132	-5.185	-1.220	-0.304	7.064	0.191	0.314	0.004	0.011	0.004	0.010	0.010	0.009	0.008	0.006
Striving Families	0.000	-4.851	-1.568	59.063	0.817	0.195	0.249	0.458	0.020	0.006	0.024	0.014	0.016	0.017	0.014	0.014
Comfortable Seniors	0.000	-1.305	-0.909	-1.569	-0.417	0.495	0.320	0.342	0.008	0.007	0.006	0.004	0.008	0.005	0.004	0.007
Countryside Communities	0.000	-5.102	-1.927	-4.899	0.806	0.653	0.672	0.445	0.012	0.014	0.014	0.012	0.015	0.006	0.008	0.025
Poorer Pensioners	0.000	-11.460	-7.839	-3.722	0.399	0.501	0.273	0.104	0.005	0.005	0.007	0.005	0.008	0.009	0.006	0.009
Young Hardship	0.000	-40.149	-24.629	-17.209	13.575	34.181	9.622	9.104	0.030	0.017	0.021	0.022	0.016	0.029	0.026	0.027
Difficult Circumstances	0.000	-5.782	-3.174	-7.146	2.422	2.360	1.981	0.905	0.038	0.025	0.029	0.051	0.046	0.064	0.053	0.046
Struggling Estates	0.000	-0.916	-4.582	6.111	0.152	0.226	0.090	0.029	0.014	0.005	0.006	0.010	0.009	0.006	0.005	0.010
Mean	0.000	-6.248	-4.251	4.825	1.084	-3.497	-0.829	0.477	0.014	0.011	0.012	0.013	0.014	0.014	0.012	0.016
Variance	0.000	9.080	5.271	24.751	3.354	27.881	7.123	2.389	0.011	0.009	0.008	0.011	0.010	0.014	0.012	0.012
Mean/Variance	0.000	-0.688	-0.807	0.195	0.323	-0.125	-0.116	0.200	1.271	1.256	1.359	1.147	1.405	0.993	0.977	1.350

Table H.17. Economic advantage E_A of using “Polynomial Interpolation” method to create a baseline for retailers and customers paying a Time-Of-Use tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-0.285	-0.265	9.040	0.138	0.083	0.058	0.055	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.001
City Sophisticates	0.000	-0.637	-0.524	-0.876	0.055	0.068	0.042	0.021	0.004	0.001	0.002	0.002	0.003	0.006	0.002	0.002
Mature Money	0.000	-2.092	-5.206	-193.600	0.568	0.491	0.298	0.219	0.010	0.006	0.005	0.011	0.008	0.009	0.008	0.010
Starting out	0.000	-0.983	-2.691	-2.870	0.819	0.462	0.274	0.158	0.010	0.019	0.009	0.020	0.021	0.013	0.009	0.009
Executive Wealth	0.000	-1.268	-28.518	-1.215	9.285	0.692	1.276	0.453	0.016	0.014	0.013	0.012	0.022	0.012	0.012	0.015
Not Private Households	0.000	-3.878	-70.627	-1.384	1.635	0.604	0.306	0.226	0.020	0.027	0.024	0.027	0.015	0.022	0.024	0.018
Steady Neighbourhoods	0.000	-1.129	-1.564	-1.783	0.316	0.073	0.045	0.052	0.013	0.013	0.006	0.007	0.015	0.017	0.011	0.017
Career Climbers	0.000	-4.123	-7.083	-5.519	0.447	1.120	0.357	0.212	0.033	0.023	0.019	0.028	0.020	0.020	0.025	0.033
Successful Suburbs	0.000	-1.841	-1.252	-1.010	2.108	-6.832	0.488	-2.027	0.005	0.019	0.008	0.011	0.004	0.006	0.006	0.018
Modest Means	0.000	-0.850	-1.357	-1.624	0.316	2.321	-0.537	-1.529	0.004	0.003	0.012	0.004	0.007	0.008	0.003	0.005
Student life	0.000	-1.273	-0.613	-1.934	-1.205	0.502	-2.900	0.304	0.004	0.008	0.005	0.010	0.006	0.004	0.005	0.004
Striving Families	0.000	-2.105	-1.516	-6.879	5.049	0.836	1.311	0.778	0.019	0.008	0.023	0.008	0.015	0.014	0.012	0.010
Comfortable Seniors	0.000	-0.582	-1634.500	-0.341	0.187	0.143	0.130	0.130	0.007	0.007	0.005	0.004	0.007	0.006	0.005	0.007
Countryside Communities	0.000	-8.216	-1.155	-0.607	0.537	0.155	0.142	0.147	0.011	0.014	0.014	0.008	0.010	0.013	0.021	0.010
Poorer Pensioners	0.000	-12.977	-34.496	-1.754	10.840	0.575	0.631	0.119	0.005	0.011	0.023	0.007	0.007	0.018	0.006	0.008
Young Hardship	0.000	-38.508	-36.785	1967.900	3.592	12.312	9.799	3.531	0.035	0.016	0.016	0.022	0.020	0.019	0.021	0.023
Difficult Circumstances	0.000	-15.893	-9.083	-3.047	11.254	3.893	4.565	4.645	0.030	0.042	0.030	0.030	0.038	0.041	0.027	0.048
Struggling Estates	0.000	-1.121	-15.033	-1.811	0.115	0.189	0.061	0.014	0.013	0.005	0.011	0.009	0.010	0.006	0.008	0.018
Mean	0.000	-5.431	-102.900	97.260	2.559	0.983	0.908	0.417	0.013	0.013	0.013	0.012	0.013	0.013	0.011	0.014
Variance	0.000	9.107	371.920	455.830	3.810	3.378	2.529	1.462	0.010	0.010	0.008	0.009	0.009	0.009	0.008	0.011
Mean/Variance	0.000	-0.596	-0.277	0.213	0.672	0.291	0.359	0.285	1.313	1.330	1.536	1.377	1.482	1.446	1.378	1.251

Table H.18. Economic advantage E_A of using "Neural Network" method to create a baseline for retailers and customers paying a Time-Of-Use tariff

Customer group	Scenario															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Lavish Lifestyles	0.000	-0.593	-0.295	-0.293	0.173	0.055	0.047	0.266	0.003	0.002	0.002	0.002	0.001	0.001	0.003	0.002
City Sophisticates	0.000	-0.395	-1.264	-0.156	0.061	0.040	0.018	0.015	0.001	0.001	0.000	0.000	0.001	0.001	0.000	0.001
Mature Money	0.000	-6.327	-2.231	-0.447	1.181	-1.311	1.591	0.394	0.003	0.002	0.002	0.005	0.002	0.002	0.001	0.003
Starting out	0.000	-2.247	-1.776	-1.882	1.482	-2.188	0.323	0.210	0.012	0.010	0.005	0.011	0.016	0.011	0.020	0.008
Executive Wealth	0.000	-19.710	-0.941	-1.534	0.638	1.155	0.609	0.444	0.015	0.010	0.018	0.013	0.015	0.013	0.010	0.013
Not Private Households	0.000	-2.642	-4.080	-8.188	3.095	0.517	1.196	0.361	0.021	0.022	0.018	0.021	0.013	0.020	0.014	0.024
Steady Neighbourhoods	0.000	-4.870	-0.407	-2.798	3.974	0.437	0.315	0.216	0.008	0.005	0.005	0.008	0.009	0.009	0.005	0.017
Career Climbers	0.000	-2.215	-1.124	-3.607	-1.428	34.407	5.522	0.527	0.025	0.021	0.021	0.020	0.012	0.016	0.017	0.023
Successful Suburbs	0.000	-3.038	-1.648	-24.097	10.319	0.271	0.334	0.143	0.006	0.007	0.004	0.007	0.003	0.004	0.006	0.034
Modest Means	0.000	-1.009	-11.960	-2.297	-0.283	0.090	0.073	0.039	0.003	0.003	0.008	0.003	0.007	0.008	0.003	0.005
Student life	0.000	-4.360	-1.071	18.587	-11.489	0.530	0.357	0.076	0.007	0.006	0.003	0.010	0.004	0.004	0.005	0.005
Striving Families	0.000	-1.638	-4.662	-0.589	0.667	0.632	0.553	0.400	0.012	0.007	0.015	0.007	0.011	0.017	0.018	0.011
Comfortable Seniors	0.000	-7.290	11.794	-2.610	0.062	0.041	0.045	0.030	0.009	0.004	0.005	0.003	0.008	0.004	0.003	0.013
Countryside Communities	0.000	-2.851	-1.315	-0.811	0.810	0.927	0.631	0.935	0.009	0.012	0.014	0.011	0.012	0.010	0.007	0.013
Poorer Pensioners	0.000	-0.885	-0.710	-1.306	2.298	42.798	0.437	0.198	0.005	0.008	0.008	0.010	0.008	0.008	0.004	0.006
Young Hardship	0.000	-35.124	-24.322	-6.123	69.408	-9.941	-6.263	7.836	0.005	0.009	0.005	0.014	0.009	0.005	0.006	0.012
Difficult Circumstances	0.000	-46.193	-15.625	-16.254	1.915	1.327	0.776	0.372	0.032	0.050	0.033	0.042	0.040	0.045	0.026	0.050
Struggling Estates	0.000	-1.959	-0.527	-0.854	15.980	-2.112	0.161	0.568	0.011	0.008	0.005	0.007	0.007	0.004	0.005	0.010
Mean	0.000	-7.964	-3.454	-3.070	5.492	3.760	0.374	0.724	0.010	0.010	0.009	0.011	0.010	0.010	0.009	0.014
Variance	0.000	12.458	7.303	8.055	16.347	12.640	2.021	1.739	0.008	0.011	0.008	0.009	0.009	0.010	0.007	0.012
Mean/Variance	0.000	-0.639	-0.473	-0.381	0.336	0.297	0.185	0.416	1.262	0.928	1.148	1.156	1.155	0.998	1.241	1.127