Highlights of Sustainability

Article

A Novel Generalised Model for Residential Energy Management System

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Abstract Disaggregated data is often used to model the cost-benefit of residential energy management systems. However, obtaining such data is time-intensive and monetarily expensive. This hinders the depth of analysis that can be done on these systems and negatively influences their large-scale uptake. This study proposes a novel generalised model of these systems that uses smart meter load profile data to model their cost-benefit. Using two years of half-hourly electricity consumption data from 5379 households in London, the model was used to examine how sociodemographic, tariff structures, and the choice of operational objectives of these systems, interact to influence their cost-benefit. The results showed that the proposed model produced reliable cost-benefit results within what is normally obtained in literature. The model demonstrated that applying one set of objectives to different customers leads to an inequitable distribution in benefits; rather, an optimal set of objectives for a given customer under a specific tariff structure can be found to produce a more equitable distribution in benefits across all customers. The proposed model is replicable and uses data that can be obtained easily and cheaply from smart meters, making it versatile for large-scale cost-benefit analysis by any electricity retailer.

Keywords residential energy management system; benefit-cost metric; load modelling

1. Introduction

An increase in electricity consumption and limited land space has made it difficult to find optimal sites to install large-scale renewable sources such as hydro-dams has made it challenging to expand the electricity grid to help to increase electricity supply [1,2]. This has led many academics and industry stakeholders to advocate the need for smart grid solutions [3]. The smart grid is meant to provide more efficient use of the grid, in part, by permitting a higher degree of demand-side management, particularly in the form of demand response [4].

Nevertheless, it was recognised that whilst electricity consumers such as residential customers were willing to change their energy consumption to benefit the environment and society, these customers did not want to spend time micromanaging electricity loads at their premises [5]. This necessitated the development of residential energy management systems [5].

Residential (or Home) energy management systems consist of computer-aided systems that are used at various levels of the grid to monitor, control, and optimise the performance of electricity production and consumption [6]. With a global market for these systems expected to reach $62.3 billion by 2023, it is noted that these systems have the potential to permit customers to improve power system reliability by participating in demand response programs, improving their energy efficiency while delivering a greater coupling between pricing schemes and customer behaviour [7,8].

Although several small-scale cost-benefit studies have provided a solid foundation for establishing the potential benefits of these systems, there are still several issues that hinder any substantial investigation into the potential large-scale benefits that customers and retailers can realise from these systems [9]. Two issues of concern for this research are the modelling approach used for these systems; and the diversity of both customers and operational objectives involved in the use of these systems.

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1.1. Need for a New Modelling Approach

When modelling these systems, a typical model consists of a power source (such as solar PV), energy consumption data of appliances, flexible load (for example electric vehicles and water heaters), objective functions for the system, constraints, and a scheduling algorithm for the system, as shown in Figure 1 [2,6,10,11].

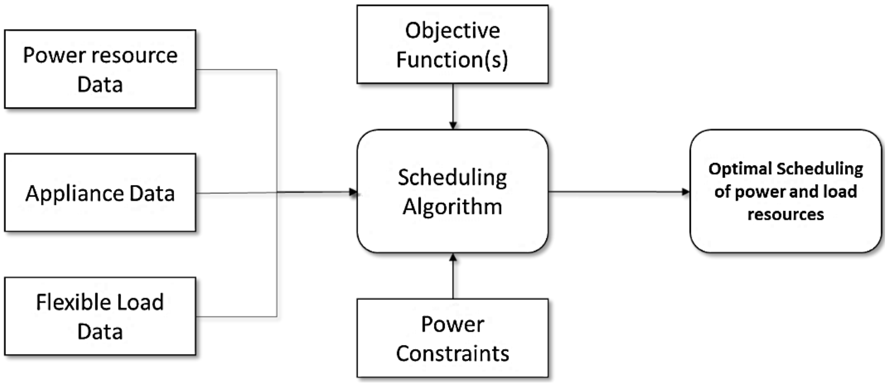

Figure 1. General interaction between parts of residential energy management systems models.

The scheduling algorithm uses the electricity consumption from appliances and flexible load and electricity production from power resources to create a schedule that would fulfil the objectives of the system within the given constraints [12,13]. Objectives could range from reducing the electricity bills of customers to social objectives such as reducing greenhouse gas emissions [14]. Whilst the modelling approach is good, it heavily relies on electricity consumption data for household appliances [15] to create optimal schedules to curtail or shift electricity use and determine the optimal demand response that a customer can provide [16].

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 [17,18]. This by extension has limited the scale and depth of analysis that can be done on the operation of residential energy management systems [19,20].

Whereas this data is readily available for a few households in online databases such as UKDALE [17], there have not been, in recent times, large-scale surveys (involving several thousand households) to capture such disaggregated data [17]. In fact, [21] compares all major publicly available disaggregated appliance data sets to reveal that one of the largest such sets has data for only 669 households ("DATAPORT"). Table 1 provides some other examples of various versions of the model and research gaps that reflect the problem expressed thus far in the modelling approach used for these systems.

Table 1. Research done on residential energy management systems and research gaps.

Components Used Systems	Objective Functions	Constraints	Research Gap	References
• Household appliance data • Battery • PV	• Minimise electricity use costs • Minimise waiting time	• Energy balance	Never indicated if approach can be used for large-scale studies.	[22]
• Household appliance data • Battery • Photovoltaics	• Minimise electricity bill	• Battery Price • Electric grid • Capacity constraints	Method required very involved analysis for only three homes.	[23]
• Household appliance data • Battery • Electric Water Heater • Photovoltaics	• Maximises customer's profit	• Performance characteristics • Response Fatigue Index • Energy balance	Stochastic analysis is only tractable for a limited number of households.	[24]
• Household appliance data	• Minimise electricity use costs • Minimise customer inconvenience	• Load levels • Ramp limits • Daily electricity uses limits	Paper is based on a single case study. No indications of whether the method can be scaled to several thousand households.	[25]

Some argue that traditional methods such as intrusive and non-intrusive techniques can be used more extensively to obtain appliance data. However, these techniques in themselves have their own disadvantages. Intrusive Load Monitoring (ILM) has the practical disadvantages of these techniques including high costs, multiple sensor configuration as well as installation complexity [26]. Non-Intrusive Load Monitoring (NILM) techniques, on the other hand, often involve intensive analysis of active and reactive power transience [26,27]. Both techniques, therefore, may not be suitable for obtaining large-scale disaggregated appliance data for simple modelling of residential energy management systems.

Given this issue, a new modelling approach would be necessary for residential energy management systems. As highlighted by [28], the purpose of these systems is to modify the load profile of a household. Therefore, it stands to reason that the presence of these systems can be modelled directly from the load profile of a household [28].

Load profiles represent the aggregate result of electricity consumption and production of the household [29]. With the wide-scale use of smart-meters and improvements in load profile modelling, large stores of household load profile data are readily available. Prominent examples of datasets that contain large stores of household energy use data are given in Table 2.

Table 2. Large sources of household energy consumption data.

Dataset	Description
Smart Meter Energy Consumption Data in London Households [30]	This dataset contains energy use readings for 5567 London Households that took part in the "Low Carbon London" project between November 2011 and February 2014.
Residential Energy Consumption Survey (RECS) [31]	A 2005 survey that collected data from 4381 households that were statistically selected to represent the 111.1 million housing units in the U.S.
German data set [32]	Load profile generator capable of producing load profiles for several thousand households using data from 60 predefined households in Germany.

From these data sets, analysis of customer energy consumption behaviour, the behaviour of smart grid technologies and modelling of load profiles using time series models such as autoregressive moving average models can easily be done [33]. However, none of these techniques have been applied in the case of modelling the behaviour of residential energy management systems.

Developing a generalised model for a residential energy management system that relies on aggregated household load profile data from existing smart meters would enable retailers to avoid unnecessary resource-intensive economic feasibility studies that are commonly undertaken to examine possible smart grid advances. The model would allow retailers to produce cost-benefit analysis that can be used to articulate benefits to customers and create marketing strategies to encourage customer participation in demand response programs. A generalised model for residential energy management systems relying solely on smart meter data can help create cost-effective benchmarks for comparing large-scale demand response projects.

1.2. Need to Address Operational Conditions of Residential Energy Management Systems

Even if such a generalised model can be created, there is still a secondary issue that needs to be addressed. Since small-scale studies have mainly focused on socially distinct customer types, different tariff types and operational objectives when modelling these systems [34], this has made it difficult to articulate the cost-benefit of these systems for large customer groups. This diversity has also made it difficult to determine the conditions that would produce an optimal demand response from residential energy management systems to maximise the benefits for a set of customers [34].

As one would expect, different customers perceive value differently and therefore will have different expectations of energy management systems [35]. In addition, sociodemographic characteristics [36] and tariff rates paid by customers [37], are two factors that influence energy use, energy management behaviour and the effectiveness of residential energy management systems.

For example, [38] used 228 households (78 paying Real-time prices and 150 paying Time-of-Use prices) to show that, customer demographics and tariff design affected how effective, energy management systems were for the overall welfare of the customer. The authors highlighted the need for an appropriate fit between customer, tariff, and system design to maximise the overall customers receive from the systems. Similarly, the authors of [39] conducted a questionnaire survey of 1913 residents in China and found that differences in sociodemographic 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 systems. Unfortunately, few attempts have been made to quantify the monetary benefits and cost that customer derives from these systems because 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 are best suited for modelling energy management systems [2]. For example, the authors of [14] examined 298 research papers that highlighted at least 10 different objectives being used to model residential energy management systems. The objectives as collated by [14] included: maximising energy bill and emissions saving, and minimising system payback period and customer discomfort. Other general objectives, such as maximising tax savings [40] and improving retailer profit [41], were also recorded in literature. However, research outlining which objective is best suited for individual customers or groups of customers is scant.

1.3. Motivation

Because this string of interrelated issues has not been comprehensively addressed, this has hindered any substantial investigation into the potential large-scale benefits that customers and retailers can realise from these systems [9]. This has had the negative effects of reducing the success rate of resource-intensive economic feasibility studies for these systems [42] and limiting customer uptake of these systems [43]. These two issues are of importance to the retailer as they can influence their financial decision-making process. Retailers wanting to advance smart grid technologies such as residential energy management systems need to be able to model their large-scale effects as quick and as cheap as possible. Therein lies the motivation of this paper.

1.4. Novelty and Contribution

Considering the potential importance of large-scale modelling of residential energy management systems, the overarching aim of this work was:

To develop a generalised model of residential energy management systems that uses household aggregated load profile data to model their large-scale cost-benefit for a diverse group of customers.

In achieving the overall aim of the research, the following major contributions were made to the state-of-the-art:

- A validated generalised model for residential energy management systems was developed using a time series equation called an "Autoregressive Integrated Moving Average" equation. The generalised model uses the load profile of a household to forecast the optimal demand response and monetary benefits that the system provides for the customer, using a cost-benefit metric (b_c). The metric itself is constructed by combining six of the most common operational objective functions, found in literature, namely: four benefit functions (electricity bill savings, emissions savings, tax savings and increase in retail profit) and two cost functions (discomfort and a simple payback period associated with the system). Using the load profile of a household to forecast the optimal demand response and monetary benefits is novel, as most researchers in the field use more expensive (and more difficult to obtain) disaggregated data to conduct such analysis.
- Past published papers do not consider the appropriateness of the objective functions used to model these systems for their selected sample of customers. This work showed that the cost-benefit provided by these systems is influenced by the optimal combination of the customers' sociodemographic profile, tariff type and the operational objectives upon which the system functions. This is a relatively new finding as most research papers on the modelling of residential energy management systems often assume only one set of objective functions without regard for sociodemographic or tariff type. This implies that many of the conclusions drawn by past research in this field may not necessarily be the most optimal.
- Finally, the generalised model was used to determine the optimal set of objective functions that should be used for different customer groups that would maximise the collective social benefit of these systems for all customers. This is highly significant and novel as it calls attention to the fact that when installing these systems on a large scale, optimising individual benefits for customers may not necessarily optimise the collective social benefit for all customers or the overall benefit the retailer receives.

The rest of this paper is devoted to providing a detailed explanation of the aim of this research was achieved and how this in turn gave rise to the major contributions mentioned.

1.5. Paper Organization

Section 2 of the paper provides the method used to collect large-scale data for over 5000 households arranged in 18 sociodemographic groups, how the residential energy management systems were modelled on a large scale and how this model in turn was used to analyse the effect of customer sociodemographic and tariff structures on the cost-benefit of these systems. Section 3 offers the results of the analysis and Section 4 presents a discussion that supports the results of the paper.

2. Method

To address the aim of this research and provide context for the study, load profile data from households that participated in the "Low Carbon London" project (UK) were chosen as the data source for analysis. The project began in April 2010 and was initiated in response to the commitment of the UK to reduce greenhouse gas emissions by 80% by 2050 [44].

One of the outcomes of the project was the classification of the 5567 households participating in the project into 18 sociodemographic groups [45] and two tariff types (Flat-rate and Time-of-Use tariff) [45]. These households were considered a representative sample of all residents in London [46]. Consequently, the project provided a large source of validated energy use data already categorised by the sociodemographic of customers and the tariff structure. A complete description of the characteristics of each group is given in Appendix A.

Since the households were scattered over a small geographic region, as highlighted in Figure 2, it was not necessary to consider the spatial distribution of the households and its effects on energy demand when examining the operation of the residential energy management systems. Consequently, this simplified the level of analysis and assumptions that had to be made in simulating the presence of these systems amongst households.

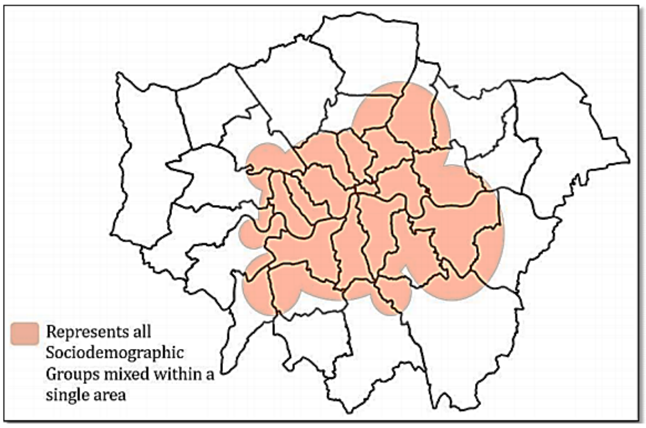

Figure 2. Distribution of 5567 households in the "Low Carbon London" Project [46].

Moreover, closing reports on the project stipulated that the sociodemographic profile of customers and the tariff customers pay influenced both peak and average electricity use [47]. This made participating households an excellent testbed for determining how the performance of residential energy management systems is jointly influenced by the sociodemographic and tariff rate.

Upon selecting the "Low Carbon London" project, of the 5567 households, data for a sample of 5379 households was available at [48]. This data consisted of half-hourly electricity consumption from April 1st, 2010, to December 31st, 2012, and was used for the analysis in this research.

The 5379 households selected were divided into 36 subgroups based on the 18 sociodemographic types and two tariff structures identified in the "Low Carbon London" project. It was noted that the hourly electricity use data for 5379 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 sociodemographic subgroups from April 1st, 2010, to December 31st, 2012, was found. Examples of these average monthly load profiles can be found in Appendix B. The result was 36 average monthly load profiles that represented the electricity use of households in the different subgroups.

After dividing the customers into 36 subgroups and finding the average monthly load profile for each subgroup, it was assumed each household had a residential energy management system installed. This was done to examine how these systems operated under different sociodemographic groups and tariff types.

Furthermore, spot price data was collected from the N2EX Great Britain power market [34] for the same period. This spot price data, along with the tariff data, enabled customer electricity bills and retail revenue to be calculated during times of demand response.

2.1. Generalised Modelling of Residential Energy Management System

Before the cost-benefit of residential energy management systems could be assessed, the behaviour of these systems needed to be characterised. Owing to the limitations of using appliance data [16], this research adopted a novel approach that used load profile data to model the operation of these systems. A conceptual model of this approach is shown in Figure 3.

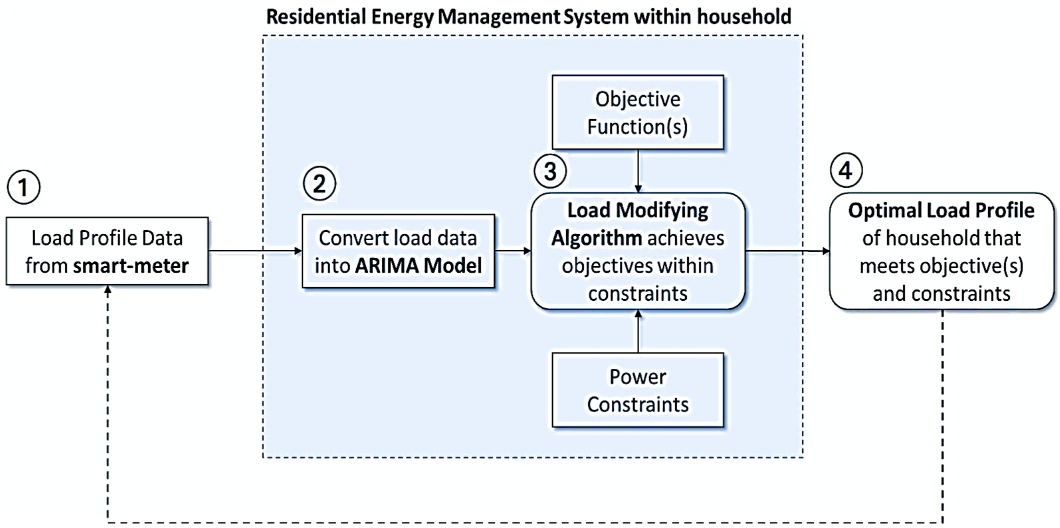

Figure 3. Conceptual model characterising the residential energy management system.

Load profile data from smart meters installed at homes (such as those installed during the "Low Carbon London" project) formed the input to the residential energy management system. This load data is converted to an "Autoregressive Moving Average" model (as indicated in step 2 of Figure 3). An "Autoregressive Moving Average" model is simply a regression equation that is based on the idea that information from the recorded past electricity use of the household can be used to forecast future electricity use [49]. An "Autoregressive Moving Average" model was chosen because it has been used frequently (with a high degree of success) as a benchmark model [49] for time series analysis and forecasting of residential electricity use. The "Autoregressive Moving Average" model, more formally ARIMA(p, d, q), is shown in Equation (1).

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

From Equation (1), the dependent variable (d_t) is the electricity use value to be forecast and the independent variables "d_{t-n}" and "e_{t-m}" are past hourly electricity use, and past hourly forecast 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 forecast error values needed to forecast "d_t". The key to representing load profile data as an "Autoregressive Moving Average" model is to find the regression coefficients of φ_n and θ_n that accurately represents the electricity use profile under consideration. In this work a statistical software package (MATLAB) was used to do this.

Equation (1) was modified to express the average and peak-to-average features of the electricity use profiles. In doing this, 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 (2):

$$d_t = \sum_{n=1}^{p} \varphi_n [A_{t-n} + Q_{t-n}] + \sum_{m=1}^{q} \theta_m . e_{t-m} \quad (2)$$

Since residential energy management systems are often required to produce a reduced percentage (k_1) in average electricity use [50], the overall effect is a reduced forecasted value (d_t) as expressed in Equation (3).

$$d_t^{**} = k_1 . \sum_{n=1}^{p} \alpha_n . A_{t-n} + k_1 \sum_{n=1}^{p} \beta_n . Q_{t-n} + k_1 . \sum_{m=1}^{q} \theta_m . e_{t-m} \quad (3)$$

Similarly, these systems can also be required to produce a reduced percentage (k_2) in hourly peak-to-average electricity use [6]. This was represented as a further reduced (${d_t}^*$) as expressed in Equation (4).

$$d_t^{*} = k_1 . \sum_{n=1}^{p} \alpha_n . A_{t-n} + k_1 . k_2 \sum_{n=1}^{p} \beta_n . Q_{t-n} + k_1 . \sum_{m=1}^{q} \theta_m . e_{t-m} \quad (4)$$

As such, Equation (4) was used to characterise the forecasted effect that residential energy management systems have on the hourly electricity consumption (d_t) of the typical households. Hence, the total reduced electricity consumed is given by Equation (5).

$$D^* = \sum_{t=1}^{T} {d_t}^* \quad (5)$$

In addition to converting the load profile to an "Autoregressive Moving Average" form, the residential energy management system model made reductions in average and peak-to-average electricity use values based on objectives and constraints that had to be specified (step 3, Figure 3). The objectives chosen for this research, although not exhaustive, covered a range of possible functions, as outlined in previous review articles [14,51]. These functions can be divided into two groups; objectives associated with maximising the benefits to the customer [51], and objectives associated with minimising the cost of having these systems [51], as shown in Table 3.

Table 3. List of objectives used in this research and references for their formulas.

Objective Functions	Formulas	Parameters	Reference
Maximise electricity bill savings (J_1): Electricity bill savings is the money the customer saves as the energy management system produces a reduced electricity demand.	$J_1 = \sum_{t=1}^{T} [(d_t - {d_t}^*) \times r_t]$		[16]
Maximise the emissions savings (J_2): Customers consuming less electricity cause power plants to produce a reduced electricity output resulting in less emissions into the environment. Emissions are the amount of greenhouse gases (primarily carbon dioxide) released into the atmosphere.	$J_2 = \sum_{t=1}^{T} [(d_t - {d_t}^*) \times c \times c_r]$	$c = 70$ £ $c_r = 0.003\ kg/kWh$	[52]
Maximise tax savings (J_3): According to [40] reduced taxes charged to the customer's electricity bill is generally given to customers that are part of a demand response program as an incentive for reduced electricity use.	$J_3 = \sum_{t=1}^{T} (\tau . d_t - \tilde{\tau} . {d_t}^*)$		[40]
Maximise retail profit (J_4): The revenue obtained by the retailer is reflected in the electricity bill of the customer. Maximising retail profit involves load shifting and this load shifting must satisfy one major condition: 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 the load is shifted from period "a" to period "b". The load shifting algorithm is given in Table C1 of Appendix C.	$J_4 = \sum_{t=1}^{T} [(d_t - {d_t}^*) \times (r_t - s_t)]$		[41,53]
Minimising customer discomfort (J_5): One of the most common is the Taguchi loss function. This function gives a relationship between the reduced consumption of a good (in this case electricity) and loss of satisfaction the consumer experiences [54].	$J_5 = \frac{X}{Z} \times Y$		[55]
Minimising payback period (J_6): Simple payback period is the amount of time taken to recover the cost of the system. The payback period "n" (given in months) is simply given as the cost of the system divided by the savings per month produced by the energy management system.	$J_6 = (p_p . J_1 - C_p)^2$	$C_p = 273.13$ £	[56,57]

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 were combined into a single benefit-cost objective function given by Equation (6). This objective function, when maximised, leads to the optimal load profile of the household.

$$Maximize\ b_c = \frac{w_1.\,J_1 + w_2.\,J_2 + w_3.\,J_3 + w_4.\,J_4}{w_5.\,J_5 + w_6.\,J_6} \tag{6}$$

where b_c, optimal benefit-cost ratio; J_1, J_2, J_3, J_4, J_5, J_6, the 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 of 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 considered during the maximisation of b_c, this weighting is 1, if it is neglected the weight is 0. Invariably, when the system is installed in a home, the customer will experience discomfort and will have to spend money over time for the installation. Therefore, for the analysis done in this research, the weights w_5 and w_6 were set at a constant value of 1 whilst all other weights can vary.

In the process of fulfilling its objectives, there are constraints that the system must adhere to. One of these constraints is that the system must not reduce electricity below the base load of the household. 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 systems such as fridges, appliances on standby, WI-FI routers and chargers. In reducing household electricity consumption, the model must ensure that the base load is still serviced. This constraint can be given by Equation (7).

$$B_t \le {d_t}^* \le d_t \tag{7}$$

Once the objectives and constraints were outlined, a load profile modifying algorithm was constructed. This algorithm specifies how the system modifies the load profile of the household (represented by the "Autoregressive Moving Average" model) to fulfil the objectives given to it while operating within constraints. The algorithm, based on particle swarm optimisation (PSO), is given in Appendix C. Particle swarm optimisation was chosen as the basis for the algorithm because it is excellent at escaping 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 [58].

The final output of the model consisted of the optimal reduced monthly load profile of the household, the values of the reduced percentage (k_1) in average electricity use, the reduced percentage (k_2) in hourly peak-to-average electricity use and the final benefit-cost ratio b_c gained from the system. In a real scenario, the optimal (reduced) load profile would form the next input of the smart meter (assuming household occupants adhered to the operation of the system).

2.2. Modelling the Effect of Customer Sociodemographic and Tariff Structures

Having developed a generalised model of a residential energy management system, it was necessary to determine how sociodemographic factors, tariff structures and the choice of objectives interact to influence the benefit, and cost, customers derive from these systems on a large scale. To do this, the 36 average load profiles representing each sociodemographic group were paired with the residential energy system model and subjected to a full-factorial analysis of variations to its objective function. In other words, the weights w_1 to w_4 given in Equation (6) were set to "1" or "0" to produce the combinations given in Table 4.

Table 4. Possible combination of objectives for a residential energy management system.

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

From Table 4 there are 16 possible combinations (or scenarios) of objectives that the system characterised in this research can have. For example, in "Scenario 12" the system is operating to achieve electricity bill savings, emissions savings for the customer and retail profit for the electricity provider (whilst considering the discomfort and cost of the system).

Each scenario was examined for each of the 36 subgroups created, to understand how the benefits and cost that these systems vary with sociodemographic, tariff structure and combination of objective functions. The steps taken to do this are given in Figure 4.

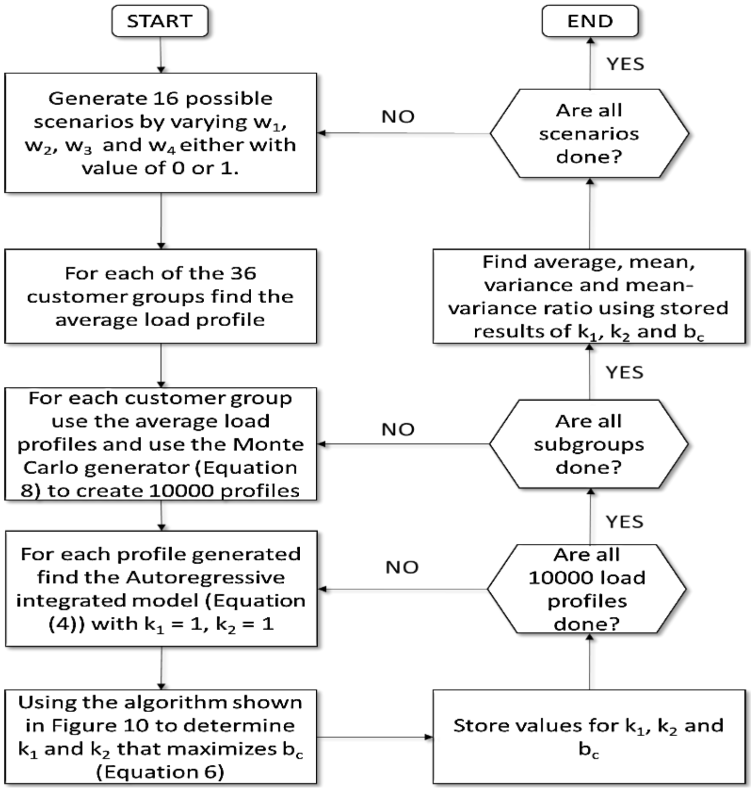

Figure 4. Method for determining effects of sociodemographic, tariff structure and combination of objective functions.

In accordance with Figure 4, the average monthly load profile created for each of the 36 sociodemographic subgroups was used in a Monte Carlo simulation. For the first sociodemographic subgroup (i.e., "Lavish Lifestyles" customers under a flat-rate tariff), the average load profile was used to generate 10,000 monthly electricity use profiles generated using a Monte Carlo generator shown in Equation (8).

$$[d_t]_m + (-1)^{round(rand)} \times [\sigma_t]_m \times rand = [d_t]_m + N \tag{8}$$

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 represented the noise associated with human activity within the home.

The Monte Carlo generator shown in Equation (8) was designed to generate random values from a normal distribution, which reflected the data for households participating in the "Low Carbon London" project [1].

For each enumerate set of objective functions, or "scenarios", (as shown in Table 4), 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) for the sociodemographic subgroup. Using the 10,000 results the average benefit-cost ratio for each subgroup was found.

Furthermore, the mean, variance, and mean-variance ratio for the benefit-cost across all sociodemographic groups and scenarios were found. The mean represents the average benefit-cost that a set of operating objectives would produce across all sociodemographic groups. The higher the mean the better the objectives are for the sociodemographic groups. The variance represents the level of equity amongst the sociodemographic groups for a given set of operational objectives. The lower the variance, the more equitable the benefits and costs are across the different sociodemographic subgroups. The mean-variance ratio represents the mean benefit for every dollar of inequity amongst the sociodemographic subgroups 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 for the residential energy management system.

On this basis, the cost-benefit values enumerated for each sociodemographic group across all scenarios were used to determine the operational objectives per customer group that would produce the highest cost-benefit value for each customer group whilst also yielding the lowest variance of cost-benefit values across these groups. This was done using the particle swarm optimisation algorithm given in Table D2 in Appendix D.

Finally, to illustrate how accurate the results are relative to research that has been done in the past, the range of values for the reduced average demand and peak-to-average demand found for all sociodemographic subgroups under flat-rate and Time-of-Use tariff structures were compared to those obtained in past literature.

3. Results

Using the average load profiles of each of the 36 sociodemographic subgroups (Appendix B provides examples for 6 out of the 36 sociodemographic subgroups) and the combinations of objective functions for the systems (scenarios), shown in Table 4, allowed the cost and benefit of the system for each sociodemographic group to be determined. Appendix E gives comparisons of the original load profile for 6 out of the 36 customer groups examined with the optimal load profiles produced by the generalised model.

The results are shown in Tables 5 and 6, where each column represents the benefit-cost ratio for all subgroups if the residential energy management system operated with only one set of operational objectives; that is, if a one-size-fits-all approach is used. As an example, column 9 (Scenario 8) from Table 6 represented the benefit-cost ratio for the 18 sociodemographic subgroups paying a Time-of-Use tariff, if the residential energy management systems operated to increase customer bill savings, emissions savings and tax savings. In Tables 5 and 6, in each scenario (or each column), the variance for the benefit-cost ratio for each set of operational objectives for the system is shown. Remembering that the greater the variance the more inequitable the cost and benefits, there is no set of objectives that produces a variance of zero (excluding the trivial scenario shown in column 1). This result is significant, as it shows that when one set of objectives is used for multiple sociodemographic subgroups the result is an inequitable distribution of benefits across the subgroups. Reflecting on this point, in Table 5 for example, the greatest variance is found for “Scenario 2” and “Scenario 3”. This means that there are some operational objectives that deliver a worse overall outcome and a more inequitable distribution of cost and benefits for customers.

This becomes even more clear when the individual rows of Tables 5 and 6 are considered. These show that there are some operational objectives that are more suitable (producing a higher cost-benefit value) for some sociodemographic subgroups than others. For example, it was clear that in Table 5 for “Steady Neighbourhoods”, Scenario 7 produced the largest benefit for the group (this scenario is where the residential energy management system operates to achieve emissions and tax savings). However, for “Career Climbers”, Scenario 8 (where the system is operated to achieve electricity bill, emissions, and tax savings) produces the largest benefit. Clearly, the sociodemographic profile should be considered with deciding the operational objectives used to operate residential energy management systems.

Table 5. Benefit Cost metric for different sociodemographic groups under the Flat-rate tariff for different operational objectives.

Sociodemographic Subgroup	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

* The values in Scenarios 9, 10, 12, 14 and 16 are not zero. However, when rounded off to 2 decimal places they appear to be zero.

Table 6. Benefit Cost metric for different sociodemographic groups under the Time-of-Use tariff for different operational objectives

Sociodemographic Subgroup	**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

Moreover, the last row of Tables 5 and 6 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 are for all sociodemographic subgroups. For example, “Scenario 5” has the highest mean benefit-cost for all the groups on a flat-rate (74.13) tariff regime, whilst Scenario 6 had the highest mean-variance for the sociodemographic groups under the Time-of-Use (105.41) tariff regime. This means that the electricity provider needs to be careful not to 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 system, the provider may not necessarily maximise the social benefits for all customers.

Moreover, when comparing the overall mean-variance (i.e., the sum of the mean-variance values) for Tables 5 and 6, the overall mean-variance is higher for a flat-rate tariff (175.07) and for a Time-of-Use tariff (103.02). This indicates that, in general, the tariff regime also needs to be given serious consideration when deciding on the design of residential energy management systems.

Having seen that both sociodemographic profile and tariff structure affect the incentives for residential energy management systems, the best set of objective functions was determined (using the algorithm shown in Table D2 in Appendix D). The results of this analysis are shown in Tables 7 and 8.

Table 7. Best combination of operational objectives that would yield most equitable distribution of benefits and cost for subgroups under a Flat-rate tariff.

Sociodemographic Subgroup	Scenario	Optimal Benefit-Cost
Lavish Lifestyles	8	2.59
City Sophisticates	8	2.42
Mature Money	7	2.42
Starting out	6	2.50
Executive Wealth	9	2.49
Not Private Households	6	2.45
Steady Neighbourhoods	8	2.48
Career Climbers	8	2.41
Successful Suburbs	9	2.47
Modest Means	6	2.46
Student life	8	2.40
Striving Families	9	2.38
Comfortable Seniors	8	2.45
Countryside Communities	6	2.46
Poorer Pensioners	9	2.51
Young Hardship	9	2.38
Difficult Circumstances	6	2.37
Struggling Estates	9	2.47
Mean		2.45
Variance		0.00
Mean-Variance		756.45

Table 8. Best combination of operational objectives that would yield most equitable distribution of benefits and cost for subgroups under a Time-of-Use tariff.

Sociodemographic Subgroup	Scenario	Optimal Cost Benefit
Lavish Lifestyles	7	2.56
City Sophisticates	7	2.49
Mature Money	6	2.45
Starting out	6	2.39
Executive Wealth	6	2.37
Not Private Households	7	2.33
Steady Neighbourhoods	7	2.38
Career Climbers	9	2.35
Successful Suburbs	9	2.39
Modest Means	8	2.34
Student life	6	2.36
Striving Families	9	2.35
Comfortable Seniors	9	2.37
Countryside Communities	9	2.36
Poorer Pensioners	6	2.31
Young Hardship	7	2.00
Difficult Circumstances	6	2.27
Struggling Estates	7	2.39
Mean		2.36
Variance		0.01
Mean-Variance		193.43

Tables 7 and 8 suggest that the highest average overall cost-benefit ratio with the lowest variance can be obtained. It is clear from Table 7 that the mean-variance obtained (756.45) was higher than the highest mean-variance (74.13) in Table 5. Therefore, finding the best set of operational objectives across the different groups produces a better result that using a one-size-fits-all approach for sociodemographic subgroups under a flat-rate tariff. Likewise, it was clear from Table 8 that the mean-variance obtained (193.43) was higher than the highest mean-variance (105.41) in Table 6. This provides a second significant insight; that the optimal set of objectives for a given customer under a specific tariff structure can be found to produce a more equitable distribution of benefits for the customers. It can be inferred from the results in Tables 7 and 8, that in deploying residential energy management systems, the retailer needs to focus on creating customer packages that help the customer obtain the best combination of price, and technology options to meet individual needs, increase customer engagement, and lead to a more equitable distribution of benefits during the technology deployment process.

Thus far, this work implies that the retailer does not necessarily need appliance-level electricity consumption data to model and analyse the possible effects (at least from the customer's perspective) of the large-scale deployment of residential energy management systems. To illustrate the validity of this, the results were compared to the range of values for the reduced average demand and peak-to-average demand found in past literature, as shown in Table 9.

Table 9. Comparing average and peak-to-average values from this work and past literature.

Tariff Type	Load Profile Change	Range of Values Found in This Work	Range of Values Found in Literature
Flat-Rate	Reduced average demand (k_1)	10% to 65%	14.7% to 65.5% [59]
	Reduced average-to-peak demand (k_2)	1% to 82%	25% to 61% [59]
Time-of-Use	Reduced average demand (k_1)	10% to 35%	7% to 50.1% [16]
	Reduced average-to-peak demand (k_2)	25% to 53%	46% to 75% [60]

The results show that the range of values in this work is comparable to those found previously. This lends support to using load profile data to model residential energy management systems performance, though it is acknowledged that it cannot indicate how appliances are to be scheduled in the home to achieve a reduced electricity demand.

The results also demonstrated that the advantage of using the current generalised model of a residential energy management system is that it enables large-scale analysis to be done quickly with reasonability and reliable results. With traditional methods of assessing the cost-benefit of residential energy management systems appliance data is usually necessary.

4. Discussion

To simplify the complexity of the model, limit the scope of the research and focus on the key issues of the paper, several assumptions were made in the initial design of the residential energy management system generalised model. These assumptions lead to limitations of the model that do provide avenues for further research.

Firstly, it was assumed that the customer strictly adheres to the optimal demand profile produced by the model; that is, changes made to the scheduling and use of appliances within the household by the system were followed by the customer. Whilst this assumption may not consistently hold, it allowed the modelling process to be simplified and is in keeping with the fact that the customer participating in a demand response program (Low Carbon Project), would have made every effort to reduce their electricity use. Relaxing this assumption would involve simulating control systems that can be used to augment the model. It is recommended that such simulation be done to further determine methods the model can be realistically enhanced.

Secondly, 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 [61] and would require extra modelling considerations that are beyond the scope of this paper. However, further research can focus on how the model can be used to assess the behaviour of different load types.

Thirdly, it was also assumed that costs such as installation cost, maintenance cost and consultation fees were not considered when examining system 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. Nevertheless, future research can be done to consider how the model can be modified to consider retail and market conditions.

Finally, it was assumed that the electricity retailer is also the aggregator responsible for aggregating the demand response of all households with the installed systems. Compensation (and penalties) paid by the aggregator for customers providing (or not providing) demand response was not considered in this research. However, this does leave room for such considerations in further research.

5. Conclusion

Large-scale adoption of residential energy management systems can potentially play a crucial role in enhancing the demand response of domestic customers. However, the diversity of customers, diversity of retail tariffs and general modelling approach used for these systems makes it difficult to model how their benefits and cost change across different customers.

A validated generalised model for residential energy management systems was developed using a time series equation called an "Autoregressive Integrated Moving Average" equation. The generalised model uses the load profile of a household to forecast the optimal demand response and monetary benefits that the system provides for the customer using a cost-benefit metric (b_c). Additionally, this work showed that the cost-benefit provided by these systems is influenced by the optimal combination of the customers' sociodemographic profile, tariff type and the operational objectives upon which the system functions. Finally, the generalised model was used to determine the optimal set of objective functions that should be used for different customer groups that would maximise the collective social benefit of these systems for all customers.

Even with these contributions recommendations for future research have also been made. These include relaxing the assumptions made in developing the model and enhancing the model with control systems algorithms.

Data Availability

The "Low Carbon London" smart meter data used in this publication can be found at: https://data.london.gov.uk/dataset/smartmeter-energy-use-data-in-london-households

Author Contributions

The contribution of each author is as follows. Peter Jean-Paul: Conceptualization; Investigation; Data curation; Methodology; Formal analysis. Tek Tjing Lie: Supervision; Validation; Review—original draft. Timothy N. Anderson: Supervision; Validation; Review—original draft. Brice Vallès: Supervision; Project administration.

Conflicts of Interest

The authors declare no conflict of interest.

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Appendix A. Sociodemographic subgroups from the "Low Carbon London" project.

Table A1. Showing description of Sociodemographic subgroups from the "Low Carbon London" Project [62].

Meta-Groups	Type	Description
Affluent	A. 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.
	B. 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.
	C. 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.
	D. City Sophisticates	Affluent younger professionals, metropolitan professionals, and socialising young renters who generally own flats in major towns and cities.
	E. 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	F. 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.
	G. 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.
	H. Steady Neighbourhoods	Home-owning families, often middle-aged, are living comfortably in suburban and urban locations.
	I. Comfortable Seniors	established communities are generally made up of retired and older empty nester couples.
	J. 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.
	K. Student life	Areas dominated by students and young people, often recent graduates.
	L. 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 with a younger than average age profile.
Adversity	M. Striving Families	low-income families typically live on traditional low-rise estates.
	N. 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.
	O. Young Hardship	Younger people who own or rent cheap small, terraced houses or flats.
	P. Struggling Estates	Low-income families living on traditional urban estates.
	Q. 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.
	U. 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. Examples of the average monthly load profiles of a typical household for 6 out of the 36 sociodemographic subgroups examined.

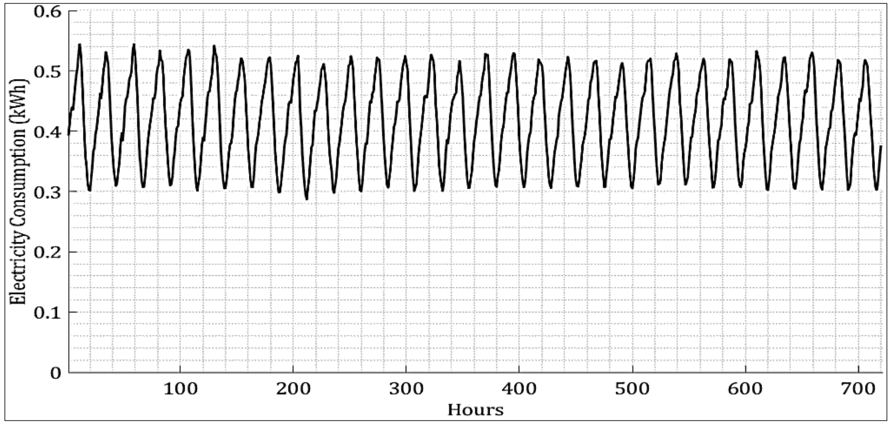

Figure B1. Average monthly Load profile for "Lavish Lifestyle" customers under a Flat-rate tariff.

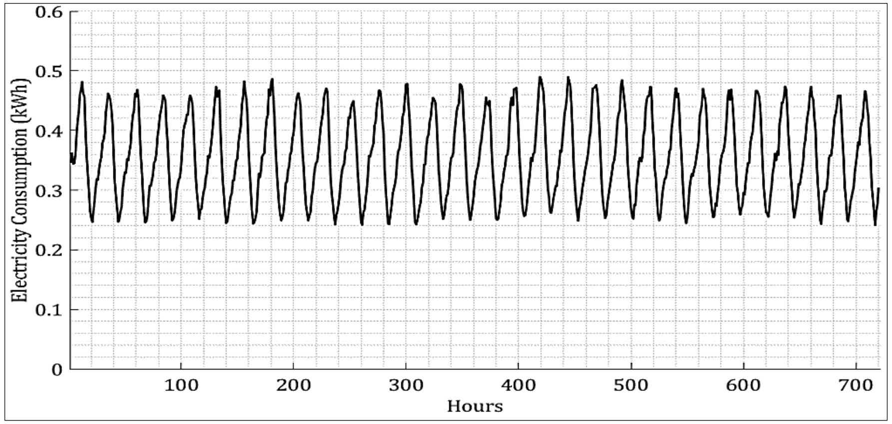

Figure B2. Average monthly Load profile for "Lavish Lifestyle" customers under a Time-of-Use tariff.

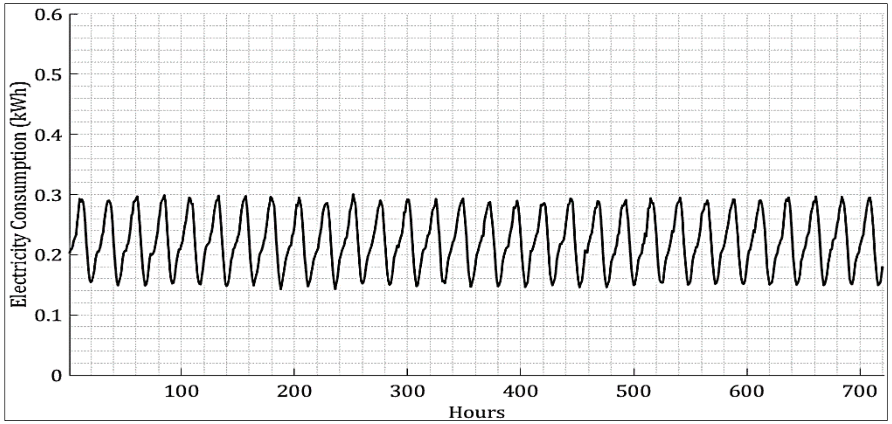

Figure B3. Average monthly Load profile for "Countryside Communities" customers under a Flat-rate tariff.

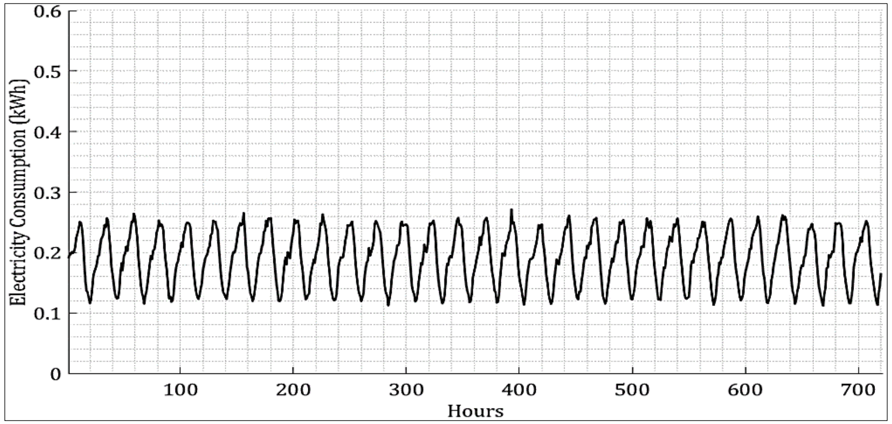

Figure B4. Average monthly Load profile for "Countryside Communities" customers under a Time-of-Use tariff.

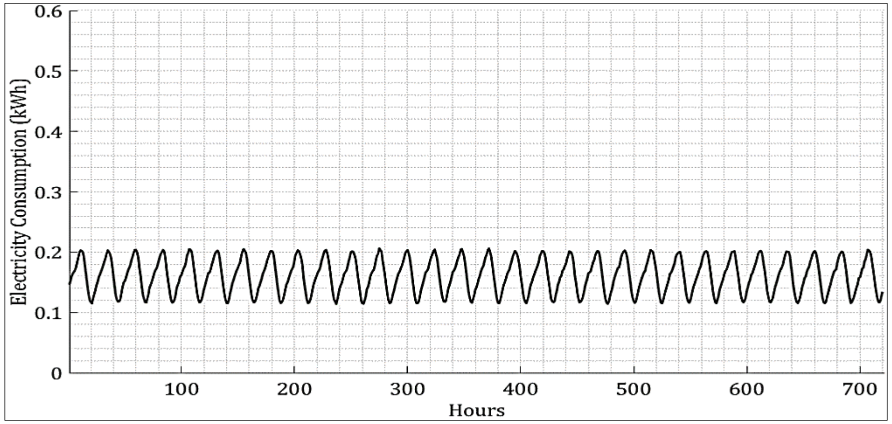

Figure B5. Average monthly Load profile for "Difficult Circumstances" customers under a Flat-rate tariff.

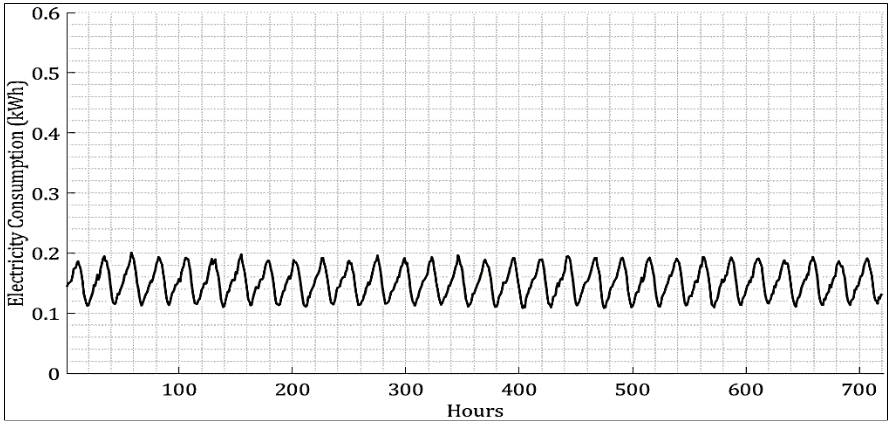

Figure B6. Average monthly Load profile for "Difficult Circumstances" customers under a Time-of-Use tariff.

Appendix C. Load modifying Algorithm.

This algorithm specifies how the system modifies the load profile of the household (represented by the autoregressive integrated moving average model) to fulfil the objectives of the system while operating within constraints.

According to the references given in Table 3, to maximise the functions J_1, J_2, J_3, J_5 and J_6 load reduction must be used. However, to maximise function J_4 (retail profit), load shifting must be used. Therefore, the load modifying algorithm was constructed to perform both load shifting and load reduction 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 $\boldsymbol{b_c}$ gained from the system. A flow chart of the algorithm is given in Figure C1.

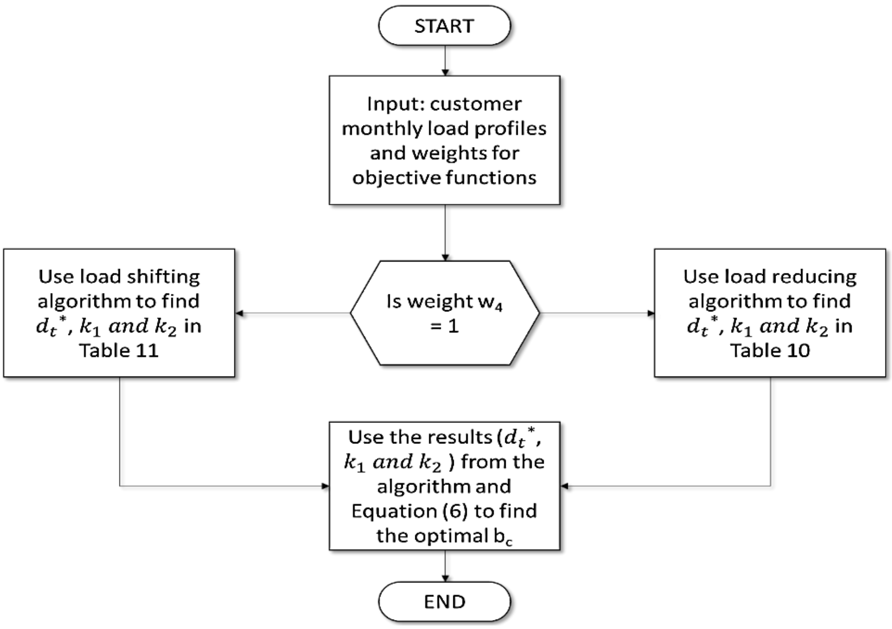

Figure C1. Flow chart of load modifying algorithm.

According to the flow chart in Figure B6, 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 system. 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 C1.

Table C1. 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" are 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 uses during hour a is greater than the electricity uses 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 use for hour "a" and hour "b".
5	New demand for hour "b" = average electricity use 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 use for hour "a".
8	New demand for hour "b" = original electricity use 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	k_1 = the average of the new forecasted demand profile divided by the average of the original forecasted demand profile.
12	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 C1, 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 C1 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 B6, 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 C2.

Table C2. Load modifying algorithm based on particle swarm optimisation.

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 [58].
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 (6). The fitness function is shown in Table C3. 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 [58].

Table C3. Fitness function for the particle swarm algorithm shown in [58].

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 (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 (4)
4	Use the new model to forecast 720 hours (1 month) of future electricity use.
5	Use the result from lines 4 and 5, Equation (6) 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 systems.

Appendix D. Other Research Algorithms.

Table D1. Algorithm for generating optimal benefit cost for each sociodemographic subgroup under each tariff for the possible cases outlined in Table 1.

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 (8)) to generate 10,000 load profiles from the representative average monthly load profile.
3	Use the algorithm given in Table 9 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 2.
6	Repeat steps 1 to 5 for the other 35 sociodemographic subgroups.
Algorithm Output: *576 average values of k_1, k_2, and b_c (one for each scenario and sociodemographic subgroup combination)*	

Table D2. Algorithm for determining the optimal objectives for each subgroup.

Algorithm Input: *576 average values of k_1, k_2 and b_c (one for each scenario and sociodemographic subgroup combination)*	
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 (18 scenario numbers (see Tables 3 and 4), one for each sociodemographic group) and velocity (rate at which the solution will change) are randomly initialised. 18 scenario numbers are used to get the b_c value for a particular scenario and sociodemographic subgroup pair.
4	Measure the fitness (the mean-variance of the b_c values obtained from the 18 scenario numbers) for each particle.
5	Store each particle best fitness 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 [58].
7	Repeat steps 3 to 6 until maximum number of iterations is reached.
Algorithm Output: *best combination of objectives for each sociodemographic subgroup that yields the maximum mean-variance for the entire sample of households.*	

Appendix E. Examples of reduced average monthly load profiles for typical households of 6 out of the 36 sociodemographic subgroups examined.

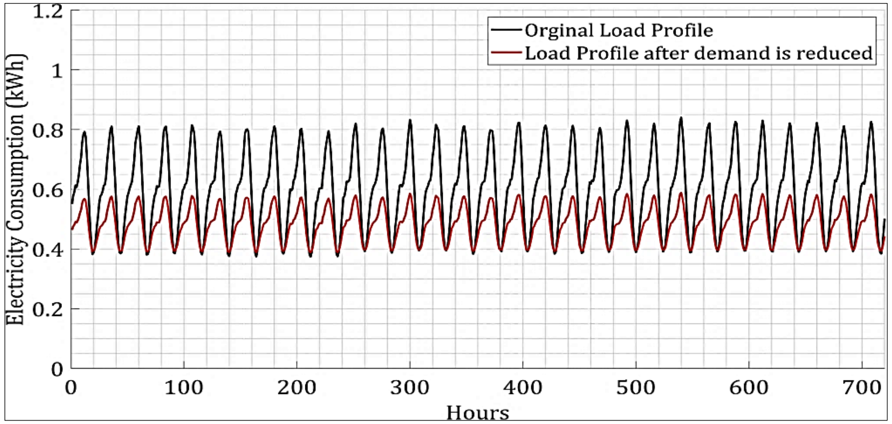

Figure E1. Comparison of normal and optimised average monthly load profile for "City Sophisticates" customers using a Flat-rate tariff under Scenario 2.

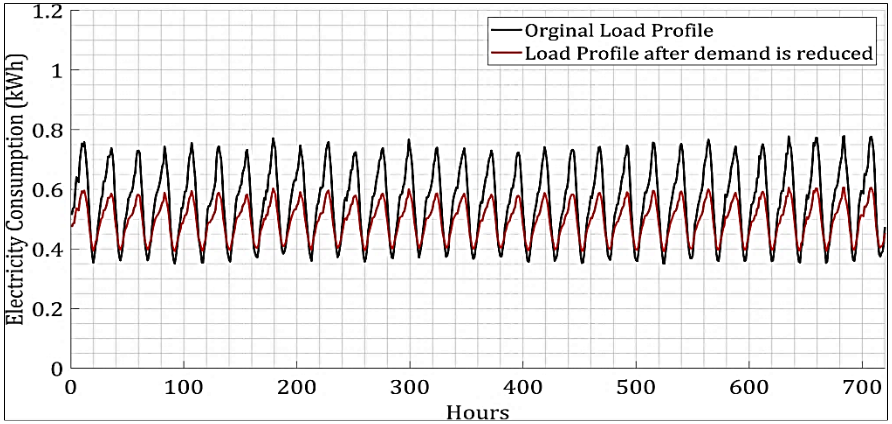

Figure E2. Comparison of normal and optimised average monthly load profile for "City Sophisticates" customers using a Time-of-Use tariff under Scenario 2.

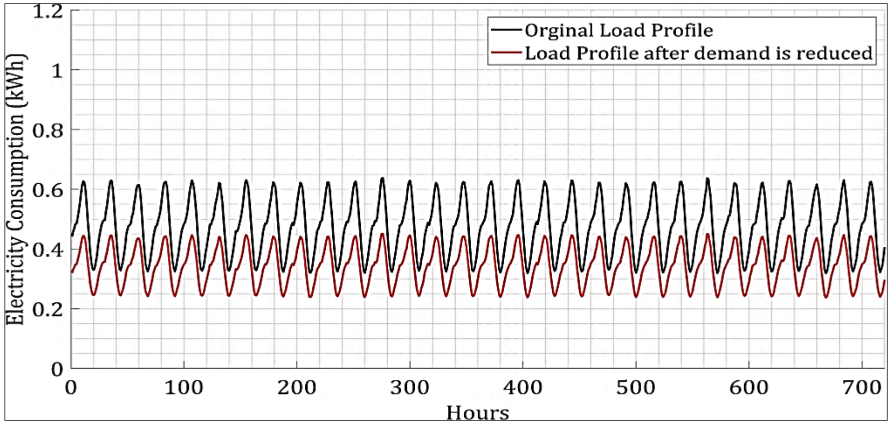

Figure E3. Comparison of normal and optimised average monthly load profile for "Steady Neighbourhoods" customers using a Flat-rate tariff under Scenario 7.

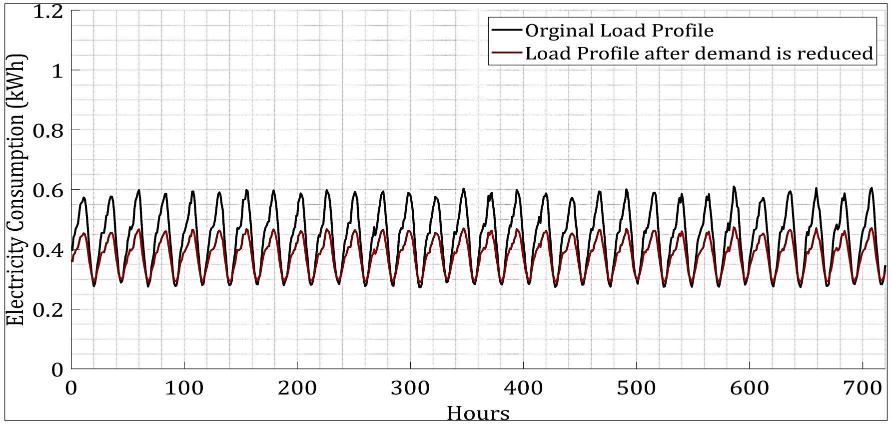

Figure E4. Comparison of normal and optimised average monthly load profile for "Steady Neighbourhoods" customers using a Time-of-Use tariff under Scenario 7.

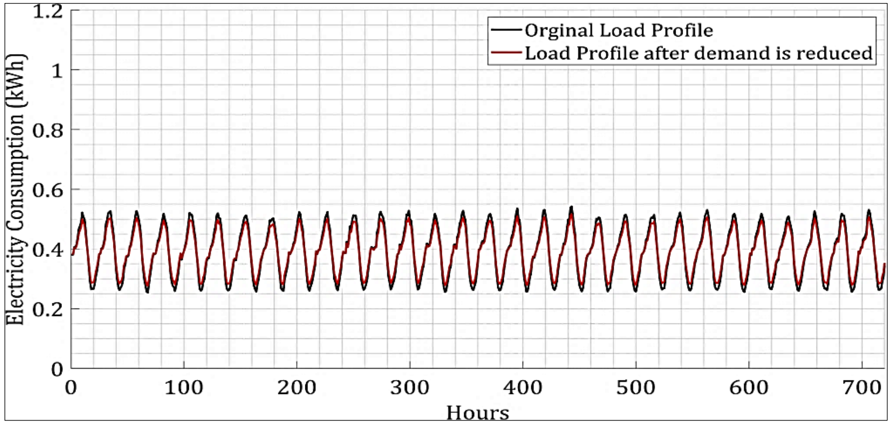

Figure E5. Comparison of normal and optimised average monthly load profile for "Poorer Pensioners" customers using a Flat-rate tariff under Scenario 14.

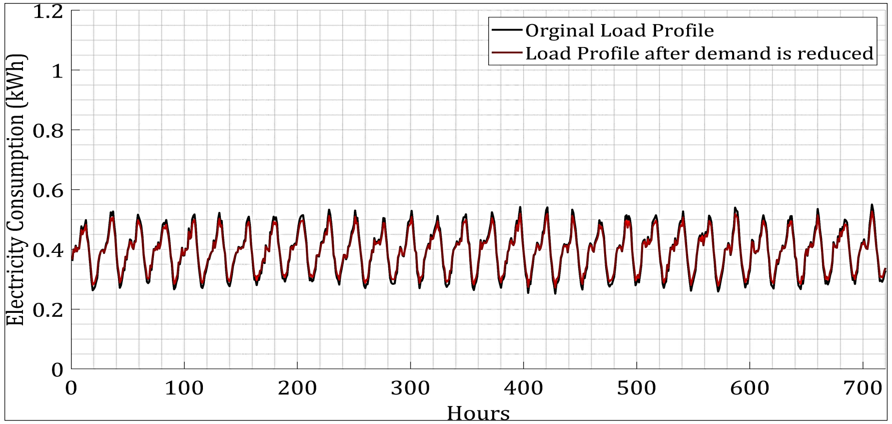

Figure E6. Comparison of normal and optimised average monthly load profile for "Poorer Pensioners" customers using a Time-of-Use tariff under Scenario 14.