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A data-driven Recommendation Tool for Sustainable Utility Service Bundles

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ABSTRACT

Managers in electric utilities face the disruption of their conventional business model of selling electricity per kilowatt-hour for invariant prices. However, the forthcoming widespread uptake of sustainable energy technologies – such as rooftop solar, batteries, heat pumps and electric vehicles – by residential customers also represents a chance for local utilities to diversify their service portfolio. To appropriately market these technologies to households, utilities need data on consumers. In this paper, we present a novel data-driven service bundle recommendation model incorporating technologies and tariffs for residential customers based on individual household data. We validate the model in a case study and quantify the utility of sharing different levels of household data. We find substantial synergies of flexible sustainable technologies and time-varying tariffs, leading to higher cost reductions for customers than tariff-switching alone that can be recommended based on easy-to-obtain data. This demonstrates a large potential for energy service bundle marketing by local utilities. The presented Machine Learning recommendation models enable more reliable recommendations than a naive benchmark. Our research thus demonstrates the potential of data-driven utility marketing strategies that focus on service bundling and the integration of customers' energy consumption data.

1. Introduction

The worldwide transition of energy systems forces electricity retailers to fundamentally change their business model. The traditional business model relies to a large extend on selling electricity for an invariant per-kilowatt-hour (kWh) tariff. This model is disrupted by new competitors and the proliferation of rooftop solar photovoltaics (PV) and home battery storage systems, with some scholars and practitioners projecting a "utility death spiral" [1]. However, cost reductions in sustainable energy technologies like solar PV, battery storage, heat pumps (HPs) and battery electric vehicles (EVs), together with improvements in information and computation technology and novel time-varying tariffs also represent a chance for power retail companies. They enable retailers to diversify their product and service portfolio, thus differentiating their offer in a highly competitive market and unlocking new revenue opportunities [2].

For retail customers, tariff switching commonly comes at the cost of searching for information, comparing offers and filling out contracts. Furthermore, tariff switching comes with an uncertainty of whether the switch will prove economically beneficial. These costs are set off by relatively small savings that can be achieved by tariff switching [2–6]. A bundle recommendation tool can decrease the switching costs and at the same time increase the potential savings for customers. In the bigger picture, this can lead to an increased adoption and use of system-beneficial time-varying electricity tariffs, smart meters and energy technologies that substitute fossil fuel based power generation, heaters and vehicles. This can yield large societal benefits by reducing system costs and emissions [2].

In summary, electricity retailers, their customers and society as a whole might benefit strongly from the combined, recurring and customized sales of bundles of electricity tariffs and electric technologies. This poses the challenge to design a corresponding recommendation tool for energy service bundles that unlocks reliable cost savings for customers and recurring cross-selling opportunities for electricity retailers.

To this end, we present a novel Machine Learning classification model for recommending cost-minimal service bundles of technology leases and tariffs to residential customers. A bundle includes a one-year subscription to an electricity tariff and an optional one-year leasing contract of different energy technologies. The model uses household characteristics and sparse historical data as inputs. The preceding labeling of the data set with the optimal tariff-technology combinations is done based on a smart home energy management system optimization. We apply this approach to a set of 292 households from London, UK to demonstrate its performance. Our results show considerable saving opportunities for customers compared to past studies, which focused

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on tariff switching alone. The best recommendation model achieves a mean accuracy of 75% and thus largely improves the accuracy of recommendations compared to a designed naive benchmark. Most interestingly, we find that high customer savings can already be achieved with input data that is easy to obtain. Acquiring high resolution smart meter data does improve recommendations, but only by a margin. This encourages the practical application of the developed approach.

The remainder of this study proceeds as follows: In Section 2, we provide a structured overview of related research and identify an important lack of bundle recommendation research in the energy context. In Section 3, we present the methodology, including the optimization of technology operation under different set-ups, subsequent label generation and finally, the classification algorithms used for recommending service bundles. In Section 4, we introduce the data set used in the case study, including data on electricity consumption, mobility, electricity prices and weather. In Section 5, we present the case study results. These results and methodical limitations are discussed in Section 6. Additionally, implications and potential extensions are sketched out. Finally, in Section 7, we summarize the main scientific conclusions and practical implications for electricity retail managers.

2. Related work

In this chapter, we outline research on decision support systems in the context of sustainable energy consumption and on recommendation tools for energy services. Furthermore, we briefly introduce the product bundling literature. Based on this review, we derive the addressed research gap.

Decision support systems intended to increase various forms of sustainability have a long research tradition (e.g. [7]). Particularly, there is a variety of studies on decision support systems in the power sector. In fact, Geelen et al. [8] propose to design services that facilitate the switch to renewable technology. In that regard, it is important to note that it has been shown that decision support systems increase decision quality [9] and are thus the right tool to aid non-experts in the transition to a more sustainable energy consumption. Similarly, Liu et al. [10] have recently pointed out that Machine Learning should be applied to increase situational awareness in an energy system dominated by uncertain intermittent renewable generation to improve its integration. Many of the corresponding decision support system applications try to address said inherent uncertainty caused by renewable generation and changing demand patterns. For instance, Ghiassi-Farrokhfal et al. [11] describe a model that reduces the risk of contracting so-called power purchase agreements, which entitle the buyer to future uncertain renewable generation at a fixed price. In principle and on a high level of abstraction, the underlying problem is similar to what we are proposing: Ensuring that a longer-term commitment in an intermittent energy system is beneficial to the investor. Other authors focus on the management of uncertainty by using decision support systems on a larger scale. Chang [12] propose a decision support system for the management of partly renewable energy systems. Similarly, Mattiussi et al. [13] propose a decision support tool based on multi-objective optimization for the management of large industrial energy systems. The authors categorize their system as model-driven according to the typology of Power [14]. Other model-driven decision support tools in the industrial context are proposed, for instance, by Allaoui et al. [15] to increase the sustainability of supply chains over a network of suppliers or by Porzio et al. [16] to make individual industrial process such as steel production more sustainable. In contrast, as there is often a lack of data availability for the power consumption of private households, we rely on what Power [14] coins a knowledge-driven approach, because our recommendations are based on knowledge of the correct labels of other consumers.

It is noteworthy that several papers propose decision support systems for subsets of the problem that we describe in this study. However, similar to Geelen et al. [8], we argue that the technological level (i.e., heat pumps replacing gas heating) needs to be connected to the service level (i.e., heat-as-a-service rather than selling an appliance) taking a more holistic approach while acknowledging the realities of data availability (i.e., high resolution energy consumption data might not be available) and customer engagement (i.e., low knowledge on energy technology). For instance, Sianaki et al. [17] and Eguiarte et al. [18] develop decision support tools that are meant to encourage manual demand response, i.e., a manual change in the consumption pattern triggered by an external signal. However, this not only requires the installation of a smart meter, it has also been shown that such manual demand response is likely not persistent [19]. There are several studies that focus on decision support regarding one specific technology out of the set of technologies that we consider comprehensively in this study. For instance, Kontopoulou et al. [20] propose a decision support system that recommends the switch to electric mobility based on driving profiles. Further studies on decision support systems for electric mobility include grid-friendly charging [21] or the installation of charging infrastructure [22]. Others have proposed decision support systems to suggest building retrofits including HVAC updates [23] or to choose the right battery storage technology for non-experts [24].

There is relatively little research on decision support systems for the choice of residential energy services such as heating, power and individual mobility services. These are particularly challenging to analyze due to the small set of products that can be combined, relatively high transaction volume per purchase, and low purchasing frequency of heating appliances, PV panels, EVs or batteries compared to other goods. These might be the reasons why, so far, no study has examined service bundle recommendation in the context of electricity retailing. Instead, studies on energy service recommendation have focused on the question whether customers should keep or switch their electricity tariff and what the corresponding savings are.

Recommendation tools are a means to reduce the information overload associated to the task of choosing from different (complex) options [25], which is particularly important in the energy domain where many households lack the necessary domain knowledge to make decisions [26]. Several papers have addressed the question of tariff selection as an isolated problem and often while assuming extensive data availability. For instance, Arora and Taylor [4] estimate probability densities for residential electricity consumption based on a broad data set from Ireland to derive static electricity cost estimates (i.e., not assuming any behavior change) under different time-varying tariffs. Similarly, vom Scheidt et al. [6] estimate the static benefits of tariff switching based on a data set from Illinois. They show that a purely naive approach of recommending tariffs based on short observed time series of consumption data is not suitable. Tostado-Véliz et al. [27] formulate an optimization problem for selecting the optimal tariff assuming full availability of high-resolution consumption data. They demonstrate their approach on one fictive household with one day of consumption but do not do out of sample testing, which makes their approach unsuitable as a decision support system. Ramchurn et al. [28] and Fischer et al. [29] develop individual consumption forecasts and on that basis, recommend specific electricity tariffs. Fischer et al. [29] additionally point out that manual demand response necessary to respond appropriately to some temporal tariff structures is perceived to outweigh possible savings, making automated control necessary. This is particularly important as customers appear to be particularly risk-averse when switching tariffs [30], which might require some form of insurance to not fall behind the status quo. Furthermore, there is a variety of studies that propose collaborative filtering for tariff selection [5,31–34]. These approaches all have in common that they assume extensive data availability down to the appliance level, do not test out of sample and disregard the recommendation of tariff-appliance combinations. The latter is specifically noted as an important extension by Zhang et al. [5]. Other authors point out that tariff selection cannot be treated as a static problem as changing economic signals also induce a change in behavior [35]. An approach that is based on similar reasoning as this study is presented by Mabuggwe and Morsi [36]. It presents a simple rule-based recommendation tool based on the Pecan Street dataset that helps in estimating expected savings based on characteristics of the load profile and appliance endowment. However, some of the features used in the model are very specific and not easily obtained, the reported expected savings are very coarse, the dynamics of demand response are only addressed by reporting a range of possible savings and the authors do not perform an out-of-sample evaluation.

Electricity tariff recommendation becomes particularly relevant with a progressing electrification of household energy demand allowing to market additional energy services such as smart meters, electric vehicles and corresponding charging points just to name a few. As pointed out by Zhang et al. [5], electrification is a major driver to make time-dependent electricity tariffs more attractive as it increases potential savings. Accordingly, our research focuses on a holistic view of household energy consumption considering various energy services. Service bundling is an active field of research, which is particularly popular for virtual goods with zero or very low marginal costs [37]. However, it is also used for physical goods [38]. Bundling describes a marketing strategy, in which two or more goods are combined to increase the customers' utility and thereby to increase the sales volume [39]. The underlying idea is that combining products can lead to a total utility that is equal or greater than the sum of the individual product utilities, which is the case for our energy service approach. The corresponding recommendations are often based on customers' historical purchase data or their relationship to or similarity with other users (i.e. collaborative filtering). For instance, Deng et al. [40] present a recommendation model for a consumer goods shopping website exploiting the social network structure of the website. Bai et al. [41] combine a decision support tool for consumer product retailers to create bundles with a recommendation tool to advertise these bundles to consumers. Pathak et al. [42] address personalized bundle generation and recommendation on video game distribution platforms. Chen et al. [43] acknowledge the difficulty of recommending bundles in an environment with a limited number of user-bundle transactions. They approach this problem by using item embeddings to approximate the bundle, while in this study, we employ a physical simulation approach as the personal utility for energy services can to some extent be based on costs. An overview of bundle recommendation research is provided in [44]. The authors list the cold start problem as a major issue, which describes the fact that upon bundle creation, no users have interacted with this product type. We overcome this issue by using a physical simulation approach that allows us to estimate the bundle utility for households. To the best of our knowledge, this is the first conceptualization and evaluation of a bundle recommendation for energy services.

In summary, past energy service recommendation research has focused on plain tariff switching. Studies have shown that savings are often too low to motivate consumers to switch, if no demand response or only manual demand response is considered. This strongly motivates to expand the existing scope of tariff recommendation to energy service bundles consisting of tariffs and sustainable energy technologies like solar PV, batteries, HPs and EVs and to include automated demand response from those technologies. This notion is further supported by the finding that the ability to perform automated demand response has a positive effect on the willingness to adopt time-varying tariffs [45]. In the case of EVs, this effect has been shown to be strongest right after the EV purchase, which further motivates a joint recommendation of technology and tariff [46]. Additionally, the accuracy of recommendations and the insurance against losses is important, as customers are risk-averse and fear negative consequences of their choices [46].

In conclusion, there is a broad stream of research on decision support tools aimed at increasing sustainable energy consumption. However, studies often focus on isolated topics (e.g. electricity tariff switching), instead of taking a holistic approach towards household energy consumption including the recommendation of energy service bundles. This is particularly damaging as several authors have found that savings from tariff switching alone are often not sufficient to encourage a behavioral shift. At the same time, the recommendation of bundles of energy services has yet to be addressed. Additionally, manual demand response is perceived to reduce utility beyond possible savings and therefore, the focus of corresponding recommendations has to be the value of automated demand response. This creates specific challenges as the unique characteristics of PV, batteries, HPs and EVs need to be captured in a model.

Furthermore, many studies assume extensive data availability and do not evaluate their approaches sufficiently. However, it is more reasonable to assume that little to no consumption data is available for specific households upon the recommendation. In this regard, it is important to differentiate between easy-to-obtain data – such as yearly consumption or sun-facing roof angle – and potentially valuable but hard-to-get data such as high-resolution load data.

To address these gaps, we present and evaluate a data-driven decision support tool for the recommendation of energy service bundles based on different levels of detail of customer data. This is specifically necessary as non-expert users are often overwhelmed by options regarding their energy consumption. The approach assumes that all recommended bundles address the same energy needs of the customers, i.e. their needs for electricity, heating and mobility and that differences in utility are a consequence of the bundles' costs. The objective of the recommendation system is consequently to recommend the bundle with the lowest annual costs for each individual customer based on household and consumption characteristics. In this study, we analyze the impact of household characteristics and data availability on the quality of the recommendations, thus contributing to research and practice.

3. Methodology

In this section, the study's methodology is presented which is aimed at recommending cost minimal energy service bundles. A bundle necessarily consists of a heating technology, a mobility technology, an electricity tariff and optionally of a solar PV plant and a battery storage. Importantly, the subscription period of the recommended service bundle is one year: All technologies are leased for the duration of one year and the contract period of the tariff is also one year. Leasing concepts for heating or PV are currently developing [47], while they are well-established for metering and vehicles. Fig. 1 shows the overall methodology. First, the sample set is generated. Second, the operation of various technology and tariff combinations in a household's home energy management system is optimized. Third, the resulting optimal operation costs and additional capital costs are used to generate the class labels for all samples. The class samples are the optimal service-tariff bundles for each household (e.g., real-time tariff with EV). Fourth, we develop and evaluate Machine Learning models that recommend optimal tariff-service bundles, i.e., derive the optimal class of each sample a priori, only using easy-to-obtain customer data and, in an alternative scenario, additional historical high-resolution consumption data.

3.1. Sample set generation

Many traditional recommender systems rely on large data sets from frequent customer transactions [44] and try to identify a bundle that delivers maximum value to a customer. Due to the cold-start problem (compare Section 2), traditional approaches are inadequate for our use case. Instead, innovative approaches are needed to create a labeled data set. Therefore, we conduct a dedicated smart home energy management optimization to create samples and labels.

This study is carried out on the basis of data from individual households. Each household is characterized by a) an empirical electricity load profile that comprises its electricity base consumption without

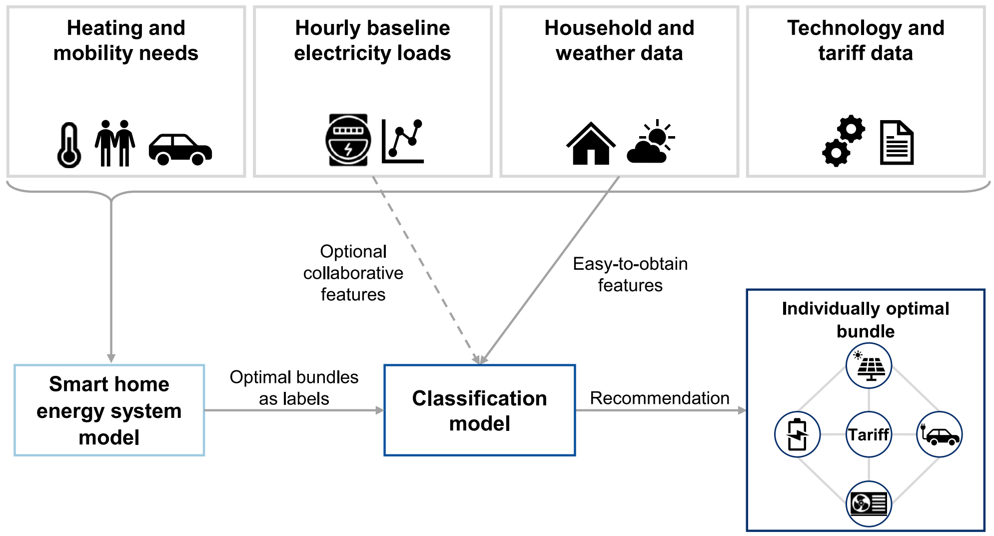

Fig. 1. Method overview.

Table 1
Morphological box of externally given circumstances.

Parameter	Values			
Azimuth	No solar possible	90°	180°	270°
Driving routine	Non-commuter	Commuter		
Vehicle	EV impossible	EV possible		
Heating	HP impossible	HP possible		

Table 2
Morphological box of service bundle design options.

Service	Design options			
Tariff	Flat	TOU-2	TOU-3	RTP
PV	PV system		No PV system	
Heating	Heat pump		Gas heating	
Mobility	Electric vehicle		Combustion engine vehicle	
Storage	Battery storage		No storage	

additional appliances such as HPs and EVs over two years at an hourly resolution and b) an empirical driving profile that captures the exact driving behavior over one week in a 15-min resolution. In addition, each household has individual characteristics that influence whether it can adopt a certain energy technology.

The most important distributed energy technologies include rooftop solar PV for the on-site generation of sustainable electricity, electric heating and electric vehicles for the direct use of electricity for domestic heating and mobility needs and home batteries for the local storage of electricity (see [48]). These technologies are therefore considered in the case study. The relevant household parameters thus include the general binary technical feasibility of an electric vehicle or electric heating in a household. For example, it could be infeasible for customers to adopt an EV because they live in an apartment and have no charging option. Besides these two parameters, households are characterized by the binary availability and azimuth (East, South, or West) of the house's rooftop and the driving routine type (existence of a commuter in the household or not). Table 1 summarizes these external parameters. By combining all given load profiles with all potential external parameter combinations, we expand and diversify the original data set and the number of samples, which enables us to derive more insights about the determining factors of optimal tariff-service bundles.

Since the mere feasibility of a certain technology does not automatically mean that its use is cost-optimal for a household, we explore a number of different bundle options for each household under the given external restrictions. Each bundle includes an electricity tariff, a heating technology (heat pump vs. gas heating), a mobility technology (EV vs. combustion engine car) and can include an optional rooftop solar PV system and an optional home battery storage. The tariff options include the four most common kinds of electricity tariffs in research and practice. These are a standard flat tariff, a time-of-use tariff with two price levels (TOU-2), a time-of-use tariff with three price levels (TOU-3) and a real-time pricing (RTP) tariff. While flat tariffs represent the predominant reference tariff for most residential customers [2], RTP tariffs link consumers' electricity prices directly to wholesale prices and thus incorporate both the risk of increased bills, and the chance for reduced bills [6,49]. Under TOU tariffs, the price levels are determined in advance and repeated at different times of the day, days of the week, or seasons and act as a proxy of RTP tariffs. Table 2 summarizes these bundle design options.

3.2. Optimization

To determine the costs of operating different tariff-service bundles for a household, we model the technology operating strategy as a mixed-integer linear program. The optimization problem minimizes the costs under each of the possible electricity tariffs that result from serving a given electricity consumption profile and the electricity demands of the HP and the EV, if applicable. For this purpose, the optimization makes use of the temporal flexibility of the applied technologies. Our optimization model is executed for all possible combinations of external characteristics and potential technologies. For example, if the external circumstances forbid usage of an EV, only bundles without EVs are considered in the optimization for the given household. In this case, we add the additional cost for gasoline to the bundle based on the driving distance of the household and average London gasoline prices (for details, see Section 4.3). If a heat pump is not applicable, we add costs for natural gas according to current retail prices in London (for details, see Section 4.3). For modeling purposes, we assume perfect foresight within one day, as there are various well-performing methods for short-term forecasting of electricity generation, loads and prices [50,51], car trips [52] and weather [53]. Besides, electricity prices for customers are often known in advance if based on day-ahead wholesale prices (like in our RTP tariff) or fixed for longer periods (like in the flat and TOU tariffs). We furthermore assume no manual demand response (e.g. switching on the dishwasher at a certain time of the day), because transaction costs of behavioral change can render manual demand response non-profitable and empirical programs have found substantially higher electricity demand elasticity for households with automated technology [54]. Capital costs (i.e., costs for leasing the technology) are included in the optimization by choosing the overall cheapest bundle consisting of operation and technology costs (for further information see Section 3.3).

The optimization uses an hourly time resolution and is performed over an entire year, for each of the two considered years individually (to find the different labels for the two years). The objective function minimizes the sum of the costs for meeting the electricity demand over all hours within the respective year (see Eq. (1)). Here, $griddemand_h$ is the amount of externally sourced electricity in hour h in kWh. It is multiplied with the price of one kWh of electricity ep_h^{tariff}, which depends on the type of tariff and hour h. The model considers compensation for the feed-in of PV-generated electricity, where $supply_h$ is the amount of electricity in kWh fed into the grid in hour h and $ep^{feedin-tariff}$ is the invariable feed-in tariff in £/kWh.[1] This compensation is subtracted from the costs of externally sourced electricity.

$$\min \sum_{h=0}^{8759} griddemand_h \cdot ep_h^{tariff} - gridsupply_h \cdot ep^{feedin-tariff} \tag{1}$$

The total hourly electricity demand consists of the inelastic base electricity use c_h^{base}, the electricity consumed by the heat pump c_h^{hp}, the electricity needed for charging the electric vehicle ch_h^{ev} and the battery storage $ch_h^{storage}$ and the part of the solar plant's generation that is fed into the grid $gridsupply_h$. Constraint (2) guarantees that the total energy demand in every hour h within the one-year period is met by the sum of the purchased electricity $griddemand_h$, the solar PV based self-generation pv_h and the energy discharged from the battery storage unit $dc_h^{storage}$. It therefore ensures that electricity demand and supply are always balanced. Moreover, the equation ensures that PV based electricity is either directly consumed, fed into the household battery for later use, or fed into the grid at a fixed feed-in compensation. For all bundles without electric heating or electric mobility, we add the costs of the non-electric alternatives to the total cost after the optimization, i.e. natural gas for bundles with gas heating and gasoline for bundles with internal combustion engine vehicles.

$$\begin{aligned} & c_h^{base} + c_h^{hp} + ch_h^{ev} + ch_h^{storage} + gridsupply_h \\ \le\ & pv_h + dch_h^{storage} + griddemand_h, \quad \forall h \in [0, 8759] \end{aligned} \tag{2}$$

In Constraints (3) and (4), the charging state of the EV $state_h^{ev}$ is defined and constrained. $evbi_{h-1}$ is a binary parameter and determines if charging of the battery is possible in hour $h-1$. This is the case, if the EV is parked at home throughout the entire hour. For each hour in which the EV leaves for a trip, the required energy for that trip is specified via dch_h^{ev}. In hours in which the EV does not leave for a trip, the required energy dch_h^{ev} is zero.

$$state_h^{ev} = state_{h-1}^{ev} - dch_{h-1}^{ev} + evbi_{h-1} \cdot ch_{h-1}^{ev}, \quad \forall h \in [1, 8759] \tag{3}$$

As it is assumed that the EV is only charged at home, $state_0^{ev}$ always needs to be sufficiently high to provide the energy for the entire following trip (Constraint (4)).

$$state_h^{ev} \ge dch_h^{ev}, \quad \forall h \in [0, 8759] \tag{4}$$

At time $h = 0$, the charging level of the car's battery storage starts at $state_0^{ev} = 0$ (Constraint (5)).

$$state_0^{ev} = 0 \tag{5}$$

The stationary battery storage's behavior is similarly described in Constraints (6) to (9). $state_h^{storage}$ is the battery storage's state of charge at hour h and depends on the charge and discharge amounts $ch_{h-1}^{storage}$ and $dch_{h-1}^{storage}$ in the previous time period $h-1$ and the previous state of charge. In the first hour, the initial charging state $state_0^{storage}$ of the battery storage is zero. Simultaneous charging and discharging of the battery is forbidden. This is important to ensure that negative prices in the RTP tariff are not unrealistically exploited. [2]

$$state_h^{storage} = state_{h-1}^{storage} + ch_{h-1}^{storage} - dch_{h-1}^{storage}, \quad \forall h \in [1, 8759] \tag{6}$$

$$state_0^{storage} = 0 \tag{7}$$

$$dch_h^{storage} \le state_h^{storage}, \quad \forall h \in [0, 8759] \tag{8}$$

$$ch_h^{storage} \cdot dch_h^{storage} = 0, \quad \forall h \in [0, 8759] \tag{9}$$

The use of the heat pump is defined in Constraints (10) to (14). Constraint (10) ensures that the heating demand of each day (hd_k) is always met. The heat generation in every hour of the corresponding day is hp_h. It depends primarily on the outdoor temperature, which is reflected in the coefficient of performance COP_h, as the efficiency of air heat pumps is lower at lower outside temperatures (Constraint (13)). For reasons of simplification, we assume that the heat pump runs on full capacity, when active. Heat generation therefore always generates a power consumption equal to the heat pump's maximum capacity hp_cap for every heating hour (Constraint (12)). Whether heating takes place in hour h is described by the binary variable $heatbi_h$. Losses in the switch-on and switch-off processes are not taken into account. To reduce the potential impact of this limitation, Constraint (11) ensures that heating is always performed consecutively within a day. In other words, the heat pump is only activated once a day and then generates the entire heat needed for the day. $nheat_h$ specifies how many hours of heating are necessary with a start in hour h to fulfill the daily heat demand hd_k. Heating storage is implicitly considered and is assumed to be operated such that the generated heat energy is distributed over the corresponding day.

$$\sum_{h=24k}^{24k+23} heatprod_h \ge hd_k, \quad \forall k \in [0, 364] \tag{10}$$

$$\sum_{x=h}^{h+nheat_h} heatbi_x \ge nheat_h \cdot (heatbi_h - heatbi_{h-1}), \quad \forall h \in [1, 8752] \tag{11}$$

$$c_h^{hp} = heatbi_h \cdot hp\_capa, \quad \forall h \in [0, 8759] \tag{12}$$

$$heatprod_h = COP_h \cdot c_h^{hp}, \quad \forall h \in [0, 8759] \tag{13}$$

$$hp_0 = 0 \tag{14}$$

The grid feed-in cannot be larger than the electricity generated by the solar PV system (Constraint (15)). Technical data and constraints of the electric vehicle and battery storage are incorporated through Constraints (16) to (19).

$$gridsupply_h \le pv_h, \quad \forall h \in [0, 8759] \tag{15}$$

$$state_h^{ev} \le state_{max}^{ev}, \quad \forall h \in [0, 8759] \tag{16}$$

$$ch_h^{ev} \le ch_{max}^{ev}, \quad \forall h \in [0, 8759] \tag{17}$$

[1] Note that, because the electricity consumption data set is from London, UK (see Section 4.1), we perform all financial calculations in British Pounds.

[2] Note that we are assuming a perfect round-trip efficiency of 100% for the battery. This is an abstraction from reality. However, in this paper, we are intending to provide a proof-of-concept for a recommendation tool for electricity tariff-service bundles. While the labels themselves might change over time as technology improves and electricity prices shift, the proposed method remains a valid approach, even though the models might have to be retrained. Small deviations of the assumptions from reality are therefore not diminishing the validity of the results of our study. It remains a subject of future work to test how the feature importance changes with changing environmental variables.

Table 3
Tuned XBG hyperparameters.

Hyperparameter	Values
Learning rate	0.001, 0.01, 0.1
Minimum child weight	1, 4, 7
Maximum depth	3, 6, 9

Table 4
Tuned ANN hyperparameters.

Hyperparameter	Values
Learning rate	0.001, 0.01, 0.1
Batch size	32, 64, 128
Number of units in dense layer	10, 30, 50

$$state_h^{storage} \leq state_{max}^{storage}, \quad \forall h \in [0, 8759] \tag{18}$$

$$ch_h^{storage} \leq ch_{max}^{storage}, \quad \forall h \in [0, 8759] \tag{19}$$

Finally, the mathematical domain of all variables is set in Constraints (20)–(23).

$$\begin{aligned} &pv_h, state_h^{ev}, state_h^{storage}, griddemand_h, gridsupply_h, c_h, ch_h^{ev}, \\ &ch_h^{storage}, ch_h^{hp}, dch_h^{ev}, dch_h^{storage}, heatprod_h \geq 0, \quad \forall h \in [0, 8759] \end{aligned} \tag{20}$$

$$evbi_h, heatbi_h, \in \{0, 1\} \quad \forall h \in [0, 8759] \tag{21}$$

$$hd_k \geq 0, \quad \forall k \in [0, 364] \tag{22}$$

$$nheat_h \in \mathbb{N}, \quad \forall h \in [0, 8752] \tag{23}$$

3.3. Label generation

Within the optimization, only the operating costs are considered. To arrive at the final total cost for each bundle, two additional steps are needed. First, capital costs for the used technologies (i.e., costs for leasing the technology) are incorporated (see Section 4.3). Second, for bundles that include non-electric alternative technologies, fuel costs are added to allow full comparability. If an electric vehicle or a heat pump are not included in a bundle in the optimization, costs for natural gas and gasoline have to be added to the extent that the same heat load and driving mileage can be covered. This makes the bundles fully comparable in regards to their costs. Based on this cost comparison, the households' cost-minimal tariff-service bundles are derived. Each household's lowest-cost bundle then represents that household's label for the subsequent classification.

3.4. Service bundle recommendation

The derived labels serve as output vector and ground truth of the recommendation models. Based on specific, limited input features, the recommendation models aim to recommend the cost-minimal bundle. Here, the recommendation of technologies means that they should be leased for the following year and the recommendation of a tariff means that it should be contracted for the following year.

We develop two models, namely an XGBoost model (XGB) and a feed-forward artificial neural network model (ANN). We assess the models in regards to statistical performance by calculating their accuracy and in regards to economic performance, by calculating the mean annual costs for customers. Along these two metrics, the models are compared to the theoretically optimal result and to a naive benchmark that simply recommends the most frequent optimal tariff-service bundle.

XGBoost is a gradient boosting based ensemble technique that has performed well in many Machine Learning challenges and delivers comparatively good results on different problem types, including on imbalanced data sets like in our case as shown in Section 5.1 [55–57]. A detailed description of the XGB model can be found in [56]. We tune three important hyperparameters via a grid search. The parameters and the tested values are displayed in Table 3.

ANN models are used in many data analytics applications in the energy context [50]. For the ANN in our study, we use an architecture with one hidden layer with a relu activation function and an output layer with a softmax activation function. We use the Adam optimizer and the categorical crossentropy loss function. Three hyperparameters are tuned using grid search, as shown in Table 4.

After comparing the performance of the two models, we select the one with better economic performance and use it to compare model performance under different feature subsets (see Section 4.4). For the comparison, we train that model once on only the basic easy-to-obtain data and once on the full data set including basic data, weather data, and four-week excerpts of smart meter data at an hourly resolution. The goal of that comparison is to identify the value of different data types.

4. Data

This chapter describes the data used within the case study in detail.

4.1. Electricity consumption profiles

The residential electricity consumption data comes from the Low Carbon London project [58]. It includes electricity consumption profiles of 324 households at half-hourly resolution from 2012 to 2013.[3] Since only private households are considered in our case study, we discard 32 outlier load profiles with an unusual low (below 1000 kWh) or high (above 10,000 kWh) annual consumption in the first year's data set. This results in a final data set of 292 electricity consumption profiles. As described in Section 3.2, these electricity consumption profiles form the basis for the construction of a total data set of 9344 households. Fig. 2 shows the average daily electricity consumption in both years. A clear seasonality can be observed, with higher electricity consumption in the colder seasons. The data patterns are similar over the two years, with the second year showing an increased level in the first months of the year. The distribution of annual electricity consumption per household is presented in Fig. 9 in the Appendix A, also showing great resemblances over both years.

4.2. Electricity tariffs

The electricity tariffs applied within this study are designed based on the wholesale electricity prices on the day-ahead market in the UK in 2018 and 2019 [59]. The data sets have an hourly resolution. This subsection provides a short overview of how the electricity tariffs for this analysis are engineered. A more detailed description can be found in Appendix B. Importantly, all tariffs are designed to be revenue neutral for utilities ceteris paribus (i.e., before demand response), as full cost recovery is a key principle in tariff design [6,49,60].

The electricity price of the flat tariff ep^{flat} is designed by calculating the sum of hourly wholesale prices $wp_{d,h}$ – with d being the day of the year and h being the hour of the day – weighted by the average hourly electricity consumption of all consumption profiles in the corresponding hour $y_{d,h}$, divided by the total annual consumption. This results in a flat tariff ep_t^{flat} of 0.059 £/kWh for the first year and 0.045 £/kWh for the second year.

[3] 2012 was a leap year and thus includes data from February 29th. To achieve better transferability and generalization of the data, the year is treated as if it was not a leap year and the corresponding 29.02.2012 data are deleted. The half-hourly data are transformed into hourly values.

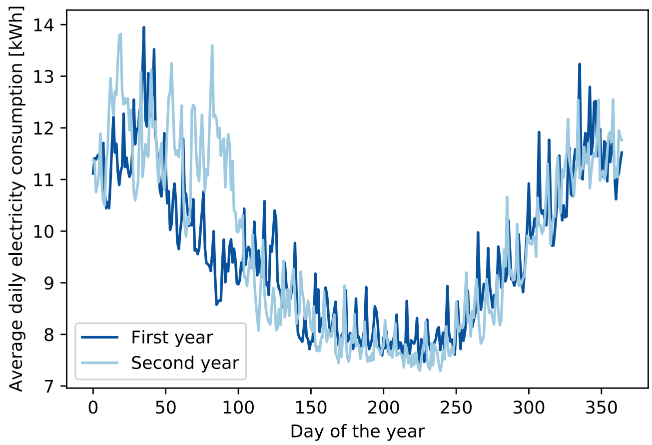

Fig. 2. Daily electricity consumption of a hypothetical average household over the course of a year.

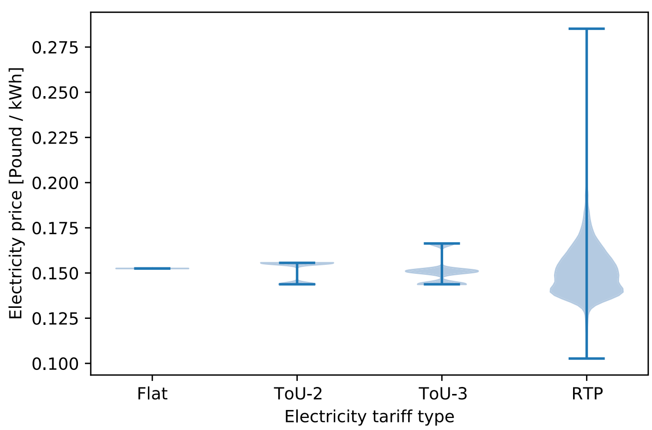

Fig. 3. Distribution of variable unit prices over electricity tariffs in the first year.

For TOU-2 and TOU-3, the tariffs are determined as weighted averages of wholesale prices and electricity consumption within the daily recurring time window.

For the TOU-2 tariff, there are two price levels, i.e. "low", between 11 pm–5 am and "high", between 6 am–10 pm, with prices of 0.05 £/kWh (0.037 £/kWh in the second year) and 0.062 £/kWh (0.048 £/kWh in the second year), respectively.

For the TOU-3 there are three price levels, i.e. "low" between 11 pm–5 am, "high" from 6 am–3 pm and again from 9 pm–10 pm and "peak", between 4 pm–8 pm, with prices of 0.05 £/kWh (0.037 £/kWh in year two), 0.057 £/kWh (0.044 £/kWh) and 0.073 £/kWh (0.056 £/kWh), respectively.

The last tariff to determine is the RTP tariff ep_t^{rtp}. Here, wholesale prices at every hour of the year wp_t are directly passed on to the consumers.

Once these wholesale based electricity tariffs are determined, grid fees, policy charges and other charges are added in order to receive the final end-user prices. In many geographies, this includes a fixed annual or monthly charge and a volumetric per-kWh charge. Therefore, we add a fixed charge of 94 £ per year, based on the actual charge in London in 2019 [61] and a volumetric charge of 0.0936 £ (0.1183 £ in year two), chosen so that the flat tariff is equal to the average variable unit price in the UK in 2018 and 2019, respectively [61]. Figs. 3 and 4 display the distribution of the final electricity unit prices for each tariff type in the first and second year, respectively.

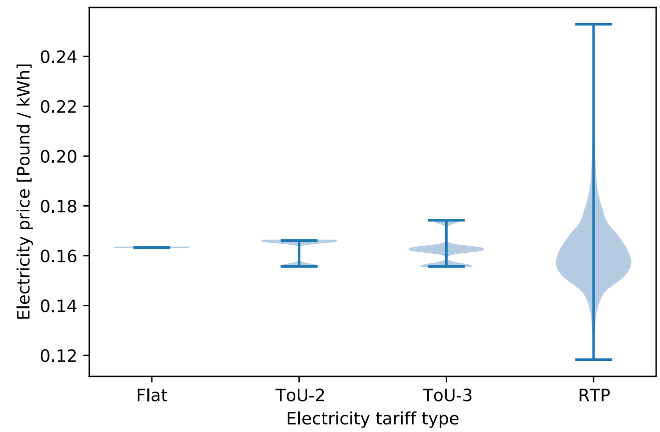

Fig. 4. Distribution of variable unit prices over electricity tariffs in the second year.

4.3. Technology data

In this subsection, the techno-economic data regarding the different energy technologies are described.

Photovoltaics

The data on electricity generation from PV systems is simulated based on Renewables.ninja [62], using historical data on PV electricity generation in London in 2012 and 2013 with an hourly resolution. A standard tilt of 25 degrees is assumed and a standard system size of 7.48 kWp is chosen, based on the average PV capacity per system installed in Great Britain in 2020 [63]. The azimuth is varied according to Table 1, resulting in three different electricity generation profiles.[4]

Battery storage

The size of the battery storage is adjusted to the average electricity consumption of the households considered here, which lies under 4000 kWh. Following the approach by Henni et al. [64], this results in an assumed battery capacity $state_{max}^{storage}$ of 6 kWh. The battery's maximum charging capacity equals the standard charging power in the UK grid of $ch_{max}^{storage} = 3$ kWh.

Heating

For serving the customers' needs for space heating and warm water, we consider an electric air-to-water heat pump with a standard power PHP of 9 kW [65]. The total heating demand of households can be estimated based on the households' annual electricity consumption in the first year and can be distributed over the year based on outdoor temperature. Thus, on heating days (i.e., days with a daily average temperature of under 12 °C [66]), the heat pump has to meet space heating and hot water demand, whereas on non-heating days it only has to meet hot water demand.[5]

[4] Following the procedure for the electricity consumption data, the data for February 29th, 2012 is deleted.

[5] More details can be found in Appendix C.

Mobility

For meeting the customers' mobility needs, we consider an EV with current technical data, i.e., a battery capacity $state^{ev}_{max}$ of 50 kWh, a maximum charging power of 11 kWh ch^{ev}_{max} and an electricity consumption of 20 kWh per 100 km [67]. In order to simulate the electricity demand of an electric vehicle, it is necessary to take mobility profiles of the households into account, which include the distances traveled, times and durations of trips by car. Since the respective mobility information of the households is not available, it is constructed based on empirical data from Ecke et al. [68]. In order to differentiate between different driving patterns, we use a commuter and a non-commuter driving profile for each power consumption profile (see Table 1).[6]

Capital and leasing costs

For generating the final labels, capital costs of the technologies need to be added to the operational costs before determining the cost-minimal bundles. In cases where a time-varying electricity tariff (TOU or RTP) is applied, the use of a smart meter is necessary. For this technology, residential customers are assumed to pay a typical annual fee of 51 £ per year in line with Gausden [69]. For a 7–8 kW PV system, the average capital costs in 2020 were 9071 £ [70].[7] These costs are discounted over the assumed lifetime of twenty years [71], assuming a weighted average cost of capital (WACC) of 4%. Similarly, the capital costs for the 6 kWh sized storage are estimated to be 2400 £, following IRENA International Renewable Energy Agency [72]. These costs are annualized based on a lifetime of ten years and a WACC of 4%. Unlike PV and battery, the heat pump is a substitute for an existing technology, in most cases conventional gas heating. Since similar costs can be assumed for both kinds of technologies, no additional acquisition costs for the heat pump are assumed. Similarly, it can be assumed that an electric vehicle is a substitute for a conventional vehicle. Since the capital costs of an electric vehicle are often still higher than those of a combustion engine car, we include additional capital costs of 4000 £, based on [73,74]. Moreover, since this case study assumes charging of the EV at home, the installation of a wallbox is necessary. This results in additional costs of 1400 £ (500 £ material costs and 900 £ installation costs), based on [75,76]. The total additional capital costs of 5400 £ are discounted over ten years with a WACC of 4% and the discounted annual rates are added to the optimization results, correspondingly.

Reference technology operation costs

To enable a fair comparison, the operation costs of alternative, non-electrical technologies for heating and mobility need to be included at a level that meets the same needs for heating and driving.

The heating costs of a gas heater can be calculated based on the average natural gas prices in London in 2018 and 2019 mapped to the two considered years [77]. Similarly to the electricity cost, they consist of a fixed yearly price and a variable unit price. This leads to yearly fixed costs of 92.51 £ for each household supplemented by operating costs of 0.0389 £/kWh in the first year and fixed costs of 99.29 £ with a unit price of 0.0394 £/kWh in the second year. The costs of operating an internal combustion engine vehicle are based on the average London gasoline prices of 2020 of 1.14 £/liter [78] and an average consumption of 7.8 liters per 100 km [79].

[6] More details can be found in Appendix D.

[7] Using a EUR:GBP conversion rate of 1:0.854.

4.4. Machine learning input data

The Machine Learning models are trained based on various input features, i.e., features that can be categorized into three groups.

The first group consists of easy-to-obtain **basic data**. This includes the households' external parameters, i.e. azimuth of roof, driving routine (i.e., the binary variable describing the existence of at least one commuting person in the household), annual electricity consumption, annually driven distance by car and binary feasibility of EV and HP, as defined in Table 1.

The second group contains **weather data** from London [58]. We use temperature, visibility and wind speed data at an hourly resolution. For each of the three, we calculate the monthly mean, standard deviation, maximum and median value.

The third group consists of **smart meter data** that customers can choose to make accessible to the retailer in order to enable them to make better recommendations ("collaborative data"). These data comprise hourly smart meter readings. To utilize those time-series data, we engineer the following features: the mean, standard deviation, maximum and median consumption of the complete time series. Additionally, the mean, maximum and standard deviation for the hour-to-hour difference are calculated and included in the feature set. Lastly, the mean for each hour of the day is aggregated to capture daily patterns.

For the Machine Learning task, the data set is split into training, validation and test sets. This split is done in two dimensions, i.e. by year and customers. All training and validation takes place on data of the first year. The subsequent evaluation takes place on data of the second year. We control that all household samples with the same underlying inelastic electricity consumption profile are assigned to only one of the three data sets (training, validation, or test) to prevent the models from learning patterns between customers that are based on the same basic consumption profile. Under this limitation, 70% of customers are randomly assigned to the training set, 15% are assigned to the validation set and 15% are assigned to the test set. We repeat the process of data splitting, model training and evaluation three times, to cross-validate our results.

The models are executed on a Windows computer with Intel i7 core, 1.80 GHz and 16 GB RAM. The average computation time for training, validating and testing is 164 s for the XGB model and 169 s for the ANN model, respectively.

5. Results

In this chapter, the results of the optimization and of the recommendation tool are presented.

5.1. Smart home energy management results — label distribution

We first evaluate the distribution of the resulting cost minimal tariff-service bundles amongst customers.

5.1.1. Bundle frequency

The combination of the four potential technology options (each of them binary) with the four potential tariffs means that 64 bundle labels are generally possible. However, most of these bundles are never optimal and thus do not occur as a label. Within the first year's optimal solution, 17 different service bundles appear (23 in the second year). The most common bundle is a flat tariff in combination with no technology, with 3932 cases (42.08%) in the first year and 4433 cases (47.44%) in the second year. This large share is driven by the fact that we deliberately design and include customer samples for whom it is externally impossible to install PV panels or use a EV or a heat pump (see Section 3.1). The second most common bundle with 1710 (18.30%) cases (1751 or 18.74% in year 2) features the use of an RTP tariff in combination with an electric vehicle. The third most frequent bundle

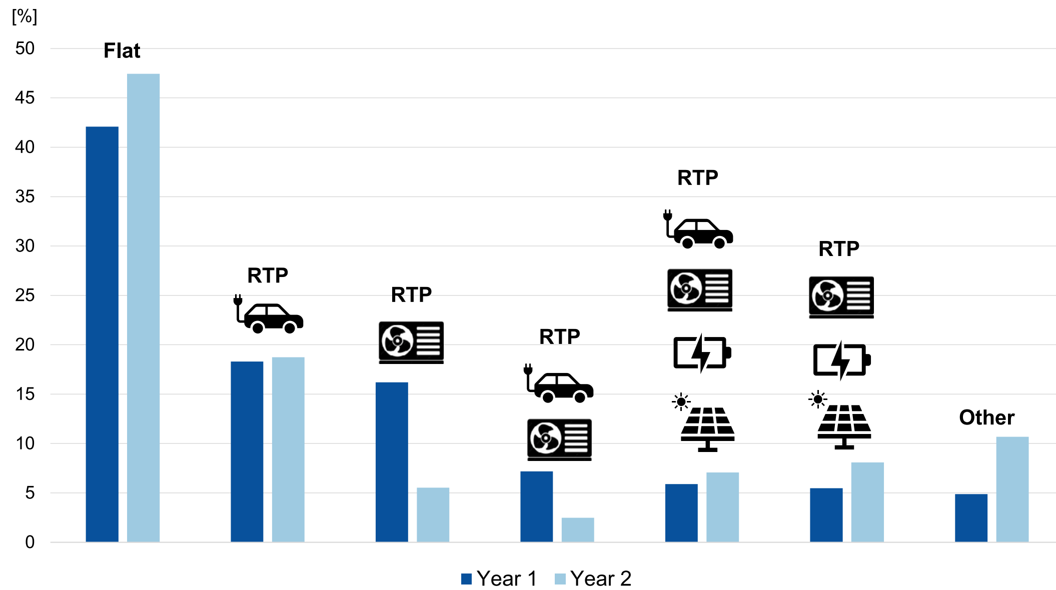

Fig. 5. Frequency of optimal bundles.

constitutes the application of a heat pump under the RTP tariff with 1513 customers (16.19%) in year 1 and 516 customers (5.52%) in year 2. An overview of these and all further bundles and their occurrences can be found in Fig. 5.

5.1.2. Individual technology and tariff frequency

Regarding the different technologies, the installation of a PV plant, independent of its azimuth, is part of the most profitable service bundle in 18.8% (27.8% in the second year) of the possible cases. Of these cases, about half include a south-facing PV system and about a quarter each include east and west facing orientation, respectively. The considerable increase in the second year is driven by higher grid electricity prices which render self-generation more attractive. The electric vehicle is part of the optimal bundle in roughly 70% of the cases in which it is externally possible, in both years. The majority of these cases belongs to customers with commuter driving profiles, which indicates that differentiating regarding driving profile types can be relevant for optimal bundle selection. The heat pump installation is part of the optimal bundle in 70.6% (49.5% in the second year) of the possible cases. The substantial drop in the second year is due to a higher median electricity price and smaller standard deviation, which renders the heat pump less financially attractive compared to its conventional alternative. This shows the value of automated demand response and the potential of time-varying tariffs. The installation of a battery storage is always possible and occurs in 14.8% (22.9%) of the cases. In the vast majority of these cases, the battery is combined with a PV system, which hints at the saving potential from self-consumption. Nevertheless, in 7.75% (15.15%) of the cases in which a battery is used, it is used without a PV system, but with the RTP tariff. In these cases, the advantage of the battery storage results solely from charging it with grid electricity in low-price hours that is later supplied to the customer behind the meter.

The standard flat tariff finds application in 42.6% (48.8%) of the most profitable service bundles. 57.4% (50.6%) and thus the majority of cases, contain the RTP-tariff. This shows the high potential of this electricity tariff. While in most cases, the combined usage of technologies renders the RTP tariff beneficial, in a few cases (0.43% in year 1 and 0.26% in year 2), the customer's electricity consumption profile alone allows the household to benefit from the RTP tariff even without additional technologies. Besides, it becomes evident that the TOU tariffs are not attractive in this model setting. TOU-2 and TOU-3 are not part of any cost-optimal bundle in the first year. In the second year, all tariffs occur, but TOU tariffs only occur in 0.61% of the optimal bundles.[8]

5.1.3. Effects of bundling on technology selection

To isolate the effect of combining electricity tariffs and technologies in bundles on the optimal recommendation, we compare these results to a scenario in which the given flat tariff is the only possible tariff option. This artificial limitation leads to results that differ in varying degrees from the tariff-service bundle recommendations. In the absence of time-varying tariffs, PV systems are chosen in 23.8% (36.6%) of the cases, constituting a small, but considerable increase. Batteries find application in 11.2% (11.8%) of the most profitable service bundles, constituting a small decrease. Notably, the use of batteries now takes place exclusively in combination with an installed PV system, since the absence of time-varying prices prohibits other applications than maximization of self-consumption. The absence of time-varying prices furthermore decreases the occurrence of EVs in the optimal bundle from roughly 70% to 65% in both years and the occurrence of heat pumps (which have even more flexibility) to 32.5% (22.0% in the second year) from 70.6% (49.5%) of cases, which constitutes a strong reduction. In summary, these comparisons demonstrate the synergies between innovative tariffs and distributed energy technologies and strongly motivate their bundled recommendation.

5.1.4. Label distribution

The retrieved optimal bundle for each household is also the label for the subsequent Machine Learning classification task. The distribution of labels is imbalanced, because some labels occur much more frequently than others. In particular, it can be a challenge (or even impossible) to adequately recommend bundles that only occur rarely or not at all in the training set of year 1.

5.2. Service bundle recommendation

This subsection presents the recommendation results of the case study. In the first paragraph, the performance of the applied Machine Learning methods is analyzed and compared to the naive benchmark

[8] In practice, additional factors such as transaction costs, simplicity and acceptance might increase the attractiveness of TOU tariffs, compared to RTP.

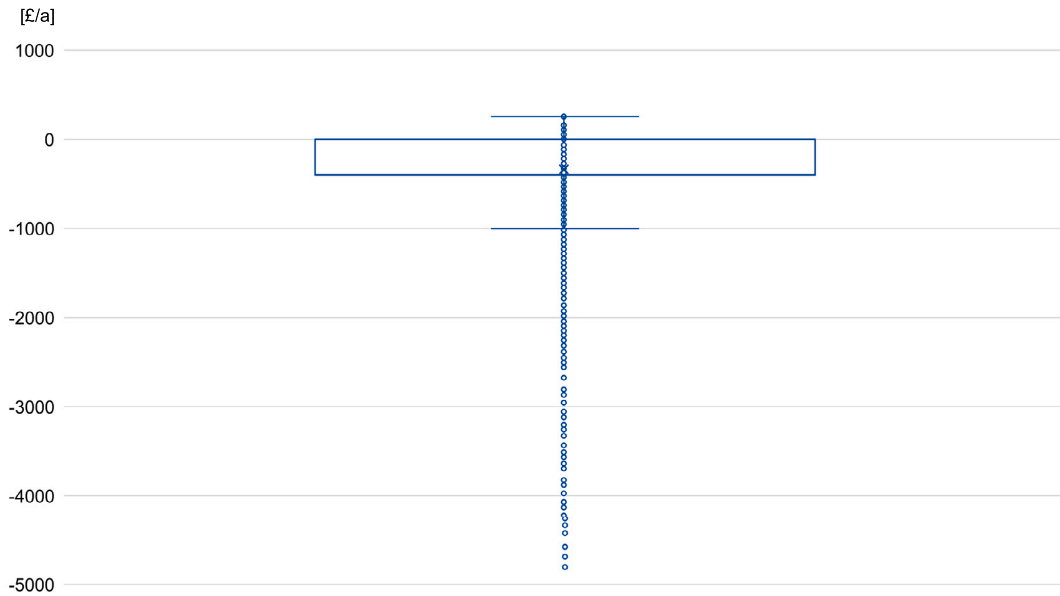

Fig. 6. Boxplot of the individual cost changes through bundle recommendation, compared to status quo (XGB algorithm with the full feature set including basic easy-to-obtain data, weather data, and smart meter data as input features).

and the optimal result both in terms of accuracy and financial implications. In the second paragraph, the performance regarding different input feature subsets is analyzed. In the third and fourth paragraph, the economic and statistical performance of the method across customers groups is analyzed in order to evaluate the method's applicability to various types of customers and to uncover possibilities for future research.

The performance is statistically evaluated with the accuracy metric, as it is the most intuitive measure to understand a classifier's performance. As the underlying data set is imbalanced, the accuracy must be evaluated in comparison to a baseline model for which we use a naive predictor. Besides accuracy, the mean economic performance is evaluated.

5.2.1. Comparison of methods

First, we compare the performance of the four methods, i.e. the two Machine Learning methods, the naive benchmark and the optimum. The calculated mean energy costs (economic evaluation) and the classification accuracies are given in Table 5. The optimal hyperparameters for each model can be found in Appendix E. The table shows that the XGB model and the ANN model outperform the naive classifier regarding classification accuracy (as a reminder: the naive benchmark is the recommendation of the default bundle, i.e. no technology and flat tariff). The ANN model achieves 73% accuracy, the XGB model 75% and the naive benchmark 56%. Besides, both Machine Learning models achieve cost reductions, compared to the naive benchmark. The ANN model achieves mean annual energy costs reductions of 316 £, while the XGB model even results in savings of 337 £. Economically, the models perform close to the theoretical optimum, with a delta of 13 £ (XGB) and 34 £ (ANN) compared to the optimal bundles. This represents a very good economic performance, even if accuracies are not too close to 100%. A potential reason for this is that the costs of some sub-optimal bundles are close to those of the optimal bundle. An analysis of the individual customers' cost changes (see boxplot in Fig. 6) shows that the vast majority of customers benefits from the recommender algorithm, compared to staying on the default bundle. Some customers can save multiple thousand pounds per year. Out of the minority of customers that receive sub-optimal recommendations, some experience increased costs, with a maximum increase of 254.77 pounds per year. This represents a risk that might prevent risk-averse residential customers from following a recommendation. To address this, an energy utility could therefore offer a cost stability guarantee to all customers and internally balance the cost reductions and increases while promoting the sustainability gain to its customers. Given that the average gains greatly outweigh the average losses, this is still economically beneficial for the utility.

Table 5
Accuracy and mean annual energy costs for different methods.

Method	Mean energy cost	Classification accuracy
Naive benchmark	2972 £	56%
ANN	2656 £	73%
XGB	2635 £	75%
Optimum benchmark	2622 £	100%

5.2.2. Comparison of feature subsets

Second, we compare the performance of using different feature subsets. As described in Section 4.4, there is a different level of difficulty in obtaining different features. Therefore, the performance with and without hard-to-obtain features is crucial to understanding their value. Table 6 shows the performance of the XGB model based on the basic easy-to-obtain features, added weather features and added smart meter high-resolution consumption features which the household can share with the energy retailer. While the XGB model achieves an accuracy of 75% when using all features, it achieves 74% without the smart meter data. Given that the naive classifier achieves an accuracy of 56%, the results imply that most of the correct classifications beyond the majority class are made possible by data that is easy to obtain. A detailed feature importance analysis confirms this. Fig. 7 shows that even if all features are available to the algorithm, the six most important features for a correct classification are the total electricity consumption in the previous year, the driving routine, the externally given feasibility of technologies and the azimuth of the solar plant. Only the seventh most important feature is based on smart meter data. Moreover, the mean costs with and without harder to obtain features differ by only 2 £, as Table 6 shows. This indicates that smart meter

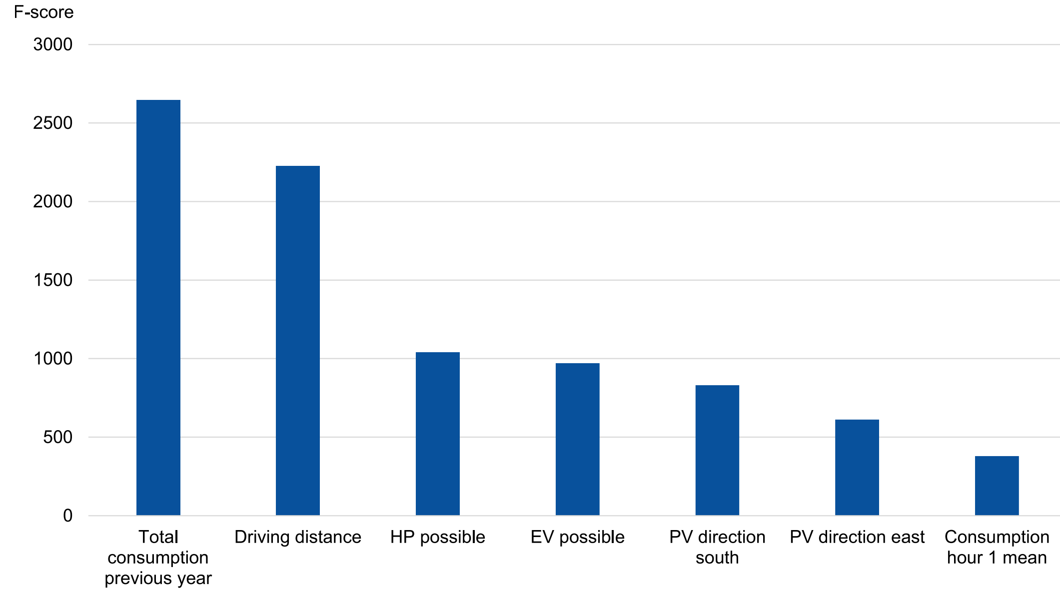

Fig. 7. Feature importance: F score of the seven most important features.

Table 6
Accuracy and mean energy costs of the XGB model with different input feature sets.

Features	Mean energy cost	Classification accuracy
Naive benchmark	2972 £	56%
Basic	2637 £	74%
Basic + weather + smart meter	2635 £	75%
Optimum benchmark	2622 £	100%

data provides little additional value for a correct classification and for savings on average.[9]

5.2.3. Comparison of customer subsets

In addition, we conduct a detailed analysis of how different customers are affected by the recommendation. As Fig. 8 displays, the recommendation algorithms achieve savings that are close to the optimum, across all customer groups. The absolute savings vary among groups. The savings are largest for customers that can lease an EV and smallest for those who cannot. Similar differences, although to a smaller magnitude, can be found between customers that can adopt heat pumps and PV and those who cannot. Having the potential to install these energy technologies unlocks higher potential savings, that are reliably identified and recommended by the Machine Learning algorithms. Another interesting aspect is that cost reductions are substantially larger for households with commuters. This is due to the higher annual driving mileage of such households that makes EVs more financially attractive, since they have lower operating costs than cars with a combustion engine. Interestingly, the finding that algorithms can already unlock most of the potential savings with the basic input data alone is not only true on average (compare Table 6), but stable across all observed customer groups. This is a very promising finding for practical application, since no extensive and expensive acquisition of weather and smart meter data is necessary for any subset of customers.

[9] Adding weather data alone to the basic data results in the same costs and accuracy as using just the basic data. Therefore, weather data alone does not provide any additional value, as is to be expected.

6. Discussion

In this section, the results of this study and its limitations are discussed, proposals for future work are given and practical implications are presented.

In summary, the proposed Machine Learning methods recommend bundles to customers that are better suited for them than the status quo. This performance is expressed by higher accuracy and lower mean costs from those models than from the naive recommender. An in-depth analysis of the results uncovers that basic input data is sufficient to achieve good performance across all customer groups. The most important input features are the household's total electricity consumption of the previous year, the annual driving mileage and the general possibility to install heat pumps, EVs and PV plants in the given household. Few customers receive wrong recommendations and thus experience an increase in costs. The risk of being among those few negatively impacted customers could deter people from following the given recommendations and thus hamper the distribution of innovative tariffs and technologies. This is especially relevant since previous studies have found that residential electricity customers are on average risk-averse (compare [46]). To cater for the risk attitude of customers, future work should investigate in more detail the option of a cost guarantee – also known as bill protection – for households, offered by the utility. The utility could apply established methods from the insurance industry to perform internal hedging of individual customers' gains and losses. This represents an interesting pathway towards practical implementability of this research.

In Section 2 we discussed that past studies on electricity tariff recommendation usually assume extensive data availability for their models. Given that we find that easy-to-obtain data is sufficient to forecast cost-reducing tariff-service bundles in most cases, these approaches is called into question and we need to hypothesize on the causal factors for this observation. However, this might be comparing apples and oranges. Tariff recommendation without technology that greatly impacts the electricity consumption needs to be done on a much more detailed level. For instance, frequently using an electric vehicle automatically makes a RTP tariff more attractive. It is therefore probable that more detailed data is simply necessary for tariff recommendation in cases with only residential baseload demand. Furthermore, we are unaware of any other study that considers the factor importance for recommending electricity tariffs. Therefore, it is also one inherent

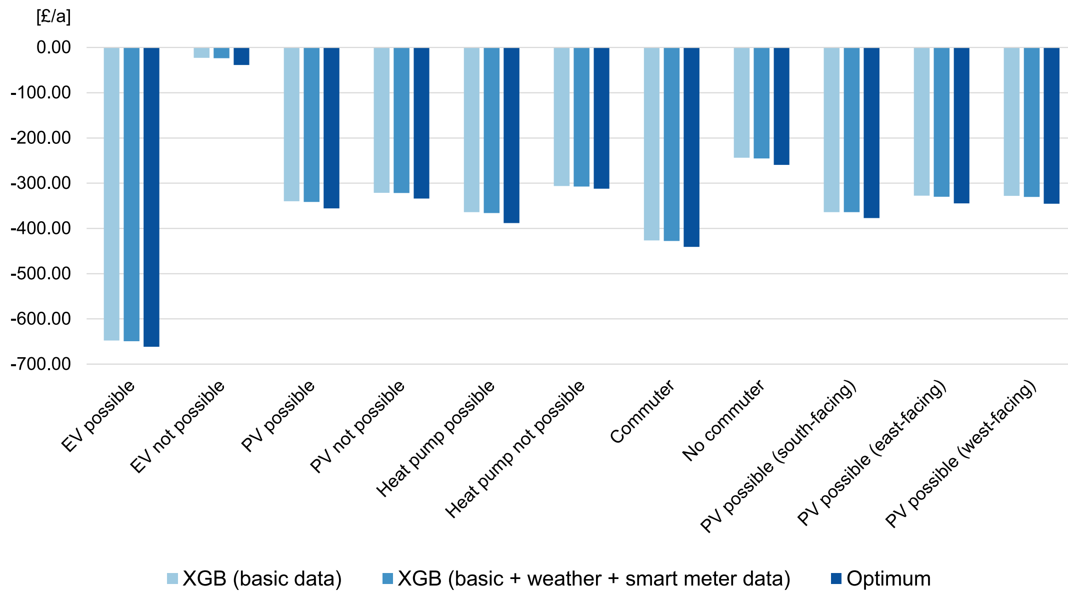

Fig. 8. Mean cost difference compared to status quo bundle (i.e. naive benchmark), by customer subset.

contribution of this study to suggest important features to decide over optimal tariff-service bundles for households.

Regarding the key limitations of this study, one can differentiate data limitations and methodological limitations.

The study is based on a data set that is subject to several limitations. All households are assumed to make use of a private car and the driving profiles are randomly assigned to the households. It is recommended to collect and use actual household specific data regarding power consumption, mobility behavior and heating demand in future work. For all technologies, assumptions and simplifications are made that might in some cases not be directly transferable to reality. Among others, the individual empirical heat consumption behavior of households is not taken into account when calculating heating requirements. Instead, average values are used. In doing so, different insulation and heat losses of the households are also not taken into account. Additionally, the technology costs assumed here are based on current state-of-the-art data and might vary in the future and be different in other geographies. Future work could expand our approach by including customized sizing of technologies based on household characteristics like number of inhabitants, house insulation, etc. Sensitivity analyses are recommended to be conducted in future work varying technology costs and their WACC. The generated labels are presumably highly dependant on the applied regulation. Consequently, changes in regulation or the application to other countries make it necessary to retrain the models. Transferring previously trained models to new settings can overcome these problems [80].

An analysis of the classification accuracy across classes unveils that the Machine Learning algorithms XGB and ANN perform specifically well for the larger classes, i.e. recommend those bundles reliably which are optimal for many customers in the training data. However, the algorithms have difficulties assigning the correct label to the smallest classes, i.e., those with only few instances. In particular, very rare classes are mostly falsely classified as one of the four most frequent classes (for an exemplary confusion matrix, see Appendix F). Uncovering this phenomenon helps making recommendations for future research, as this phenomenon is a typically problem for Machine Learning algorithms when applied to imbalanced data sets. It is therefore recommended to apply well understood counter measures, such as oversampling, undersampling, and acquisition of larger data sets, in future extensions of this study or practical implementation.

However, the specific suitability of the chosen algorithms also is subject to future research. We have chosen these two algorithms as they are frequently used in the energy research domain [50]. Furthermore, as the results are close to the optimum (see Fig. 8), we refrained from testing further methods as a complete review of available classification methods is out of the scope of this paper. However, other classification methods could be superior in identifying rare classes. Furthermore, we do not explore ensemble methods in detail beyond the use of the XGB algorithm. A well-crafted approach using ensemble learners might also be superior in terms of identifying rare classes. Therefore, as we cannot claim superiority of our methods, this remains an interesting topic for future research. In this study, provide a proof-of-concept that is independent of these limitations.

The optimization and recommendation methods are also subject to limitations. Our study only takes automated demand response into account for the electricity consumption of newly installed technology. In addition, we focus on costs as the only metric for identifying optimal tariff-service bundles and for making recommendations. Transaction costs and behavioral considerations that might influence customers' decisions [81,82] are ignored. Manual demand response is neglected, as it typically represents a smaller potential than the automated demand response of technologies such as electric vehicles and heat pumps in our study. As Schneider and Sunstein [54] point out, it can be beneficial to use RTP tariffs for technologies with automated demand response and in parallel TOU tariffs for all manually operated electricity consumption. Such manual demand response could be modeled according to Gottwalt et al. [3] in future expansions of this study.

7. Conclusions

Our results demonstrate the benefits of energy service bundles that combine time-varying electricity tariffs with flexible sustainable technologies. Moreover, we demonstrate the value of corresponding recommendation systems. We find considerable saving potentials that by far exceed the savings that customers can achieve from tariff switching alone. The availability of time-varying electricity tariffs makes energy technologies more financially attractive for many households. In the vast majority of cases, the optimal bundles do not only include a change of tariff.

In detail, our results show that the developed Machine Learning recommendation models achieve accuracies of 73%–75% and thus outperform the naive benchmark (56%). Similarly, they achieve better economic performance, by reducing mean energy costs to 2635–2656 £, compared to 2972£ under the naive benchmark. On a single customer level, the recommendation models enable savings for the vast majority of customers, especially for those that have the potential to install a heat pump, or a PV plant, or use an electric vehicle and for those that have a commuter living in the household. In order to cater for risk-averse customers who fear cost increases, we propose a bill protection mechanism to be offered by the energy utility.

Moreover, we find that the proposed models can achieve these cost reductions largely by using data that is easy to obtain. The data with the highest feature importance are the total electricity consumption of the previous year and the annual driving mileage. Using additional granular smart meter data does improve the results across all observed customer groups, but only by a margin. This finding supports the practical applicability of the proposed method.

In summary, the developed decision support tool can help customers to find a personalized tariff-service bundle that lets them benefit from cost savings. At the same time, this increases the diffusion of sustainable energy technologies, efficient tariffs and smart meters, which can be a strong digital support for the energy transition. The proposed tool may help electricity retailers in their business model transition, highlighting investments that are beneficial and helping them to profit from the ongoing decentralization of the energy sector. Based on our results, we see great potential for further development and application of Machine Learning based recommendation systems, combining the recommendation of tariffs and energy services as a bundle.

CRediT authorship contribution statement

Frederik vom Scheidt: Conceptualization, Data curation, Formal analysis, Methodology, Software, Investigation, Validation, Visualization, Writing – original draft, Writing – review & editing. **Philipp Staudt:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data used for this paper is available at github.com/PhilippStaudt/UtilityServiceBundlesData.

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Appendix A. Consumption data

Among the electricity consumption profiles, a minimum annual consumption of 1,026.50 kWh and a maximum value of 9,753.05 kWh can be observed, in the first year. In the second year, the annual consumption is between 1,001.91 kWh and 11,500.73 kWh. Fig. 9 displays the distribution of the annual consumption values.

Appendix B. Electricity tariffs

In the data of 2018, two data points are missing. In 2019, 26 data points are missing. They are supplemented by linear interpolation. Fig. 10 shows the distribution of wholesale electricity prices in 2018 across the hours of a day in the form of box plots. Fig. 11 illustrates the distribution of the same data in 2019. For the application, the price data of 2018 is linked to the consumption data of 2012 to form the first year's data and the 2019 price data is linked to the 2013 consumption data to form the second year's data.

Eq. (24) defines the calculation of the electricity price for the flat tariff ep^{flat}.

$$ep_t^{flat} = \frac{\sum_{d=1}^{365} \sum_{h=1}^{24} wp_{d,h} \cdot y_{d,h}}{\sum_{d=1}^{365} \sum_{h=1}^{24} y_{d,h}}, \quad t \in [1, 8760] \tag{24}$$

For the TOU-2 tariff, the energy prices are determined according to (25) and (26). Eq. (27) sets the time periods in which these prices occur.

$$ep^{tou2,l1} = \frac{\sum_{d=1}^{365} (\sum_{h=1}^{6} wp_{d,h} \cdot y_{d,h} + \sum_{h=23}^{24} wp_{d,h} \cdot y_{d,h})}{\sum_{d=1}^{365} (\sum_{h=1}^{6} y_{d,h} + \sum_{h=23}^{24} y_{d,h})} \tag{25}$$

$$ep^{tou2,l2} = \frac{\sum_{d=1}^{365} \sum_{h=7}^{22} wp_{d,h} \cdot y_{d,h}}{\sum_{d=1}^{365} \sum_{h=7}^{22} y_{d,h}} \tag{26}$$

$$ep_t^{tou2} = \begin{cases} ep^{tou2,l1}, & \text{if } t \in [24k+1, 24k+6] \\ & \bigcup [24k+23, 24k+24] \\ & \text{with } k \in [0, 364] \\ ep^{tou2,l2}, & \text{if } t \in [24k+7, 24k+22] \\ & \text{with } k \in [0, 364] \end{cases} \tag{27}$$

The calculation of the three TOU-3 price levels is conducted similarly to the TOU-2, as shown in Eqs. (28), (29) and (30). Eq. (31) sets the time periods in which these prices occur.

$$ep^{tou3,l1} = \frac{\sum_{d=1}^{365} (\sum_{h=1}^{6} wp_{d,h} \cdot y_{d,h} + \sum_{h=23}^{24} wp_{d,h} \cdot y_{d,h})}{\sum_{d=1}^{365} (\sum_{h=1}^{6} y_{d,h} + \sum_{h=23}^{24} y_{d,h})} \tag{28}$$

$$ep^{tou3,l2} = \frac{\sum_{d=1}^{365} (\sum_{h=7}^{16} wp_{d,h} \cdot y_{d,h} + \sum_{h=20}^{22} wp_{d,h} \cdot y_{d,h})}{\sum_{d=1}^{365} (\sum_{h=7}^{16} y_{d,h} + \sum_{h=20}^{22} y_{d,h})} \tag{29}$$

$$ep^{tou3,l3} = \frac{\sum_{d=1}^{365} \sum_{h=17}^{20} wp_{d,h} \cdot y_{d,h}}{\sum_{d=1}^{365} \sum_{h=17}^{20} y_{d,h}} \tag{30}$$

$$ep_t^{tou3} = \begin{cases} ep^{tou3,l1}, & \text{if } t \in [24k+1, 24k+6] \\ & \bigcup [24k+23, 24k+24] \\ & \text{with } k \in [0, 364] \\ ep^{tou3,l2}, & \text{if } t \in [24k+7, 24k+16] \\ & \bigcup [24k+21, 24k+22] \\ & \text{with } k \in [0, 364] \\ ep^{tou3,l3}, & \text{if } t \in [24k+17, 24k+21] \\ & \text{with } k \in [0, 364] \end{cases} \tag{31}$$

The last tariff to determine is the RTP tariff ep_t^{rtp}. Here, wholesale prices at every hour of the year wp_t are directly passed on to the consumers, as shown in Eq. (32).

$$ep_t^{rtp} = wp_t, \quad t \in [1, 8760] \tag{32}$$

Appendix C. Heating

The total heating demand of households can be estimated based on the number of inhabitants and the size of the living space. Since this data is not included in the original electricity consumption data set, it is estimated based on the households' annual electricity consumption in the first year, divided by the average electricity consumption in the

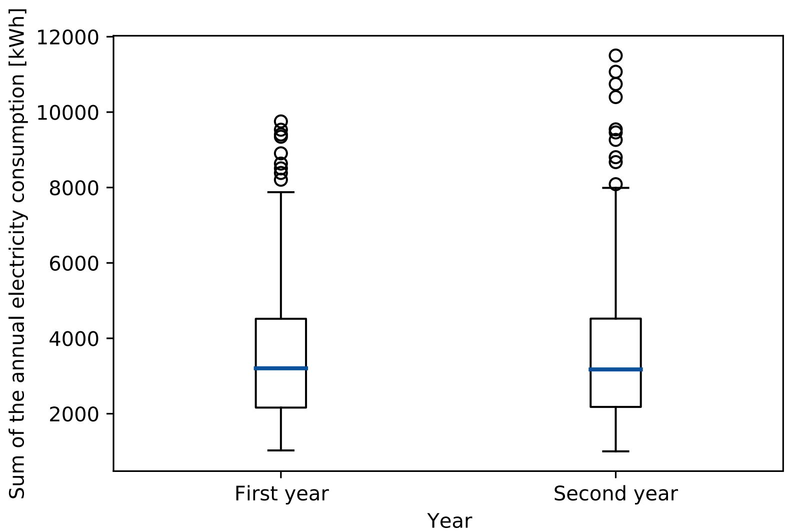

Fig. 9. Distribution of the annual electricity consumption of the households.

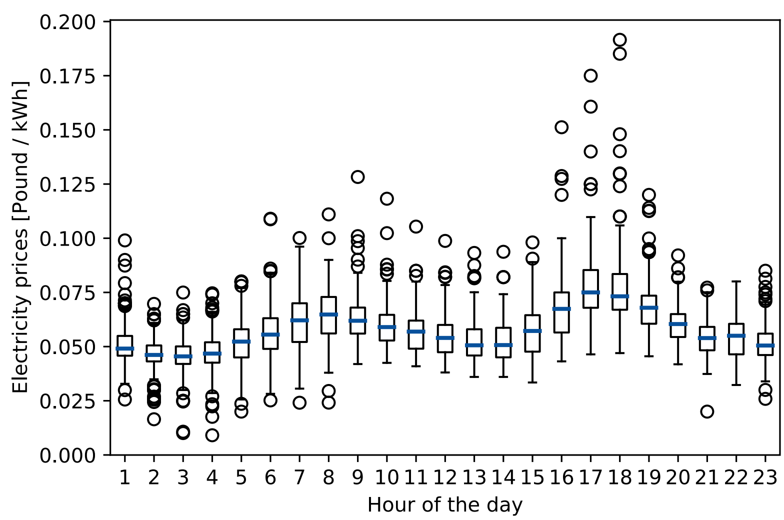

Fig. 10. First year's hourly electricity wholesale prices in the UK throughout the day.

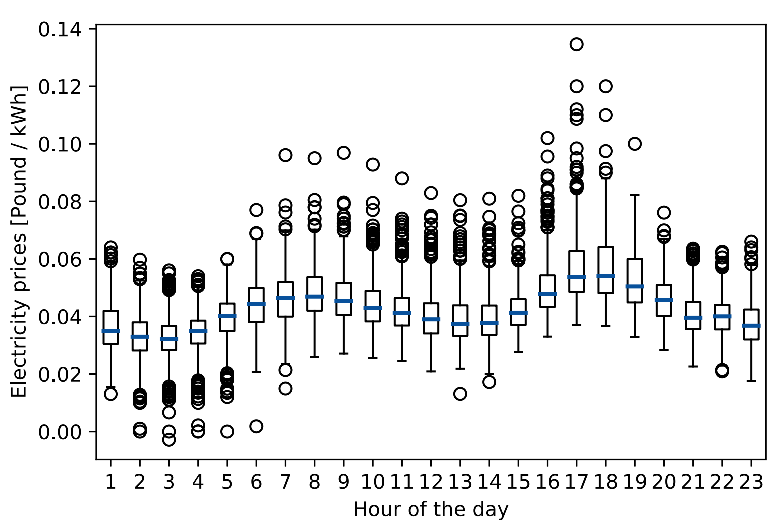

Fig. 11. Second year's hourly electricity wholesale prices in the UK throughout the day.

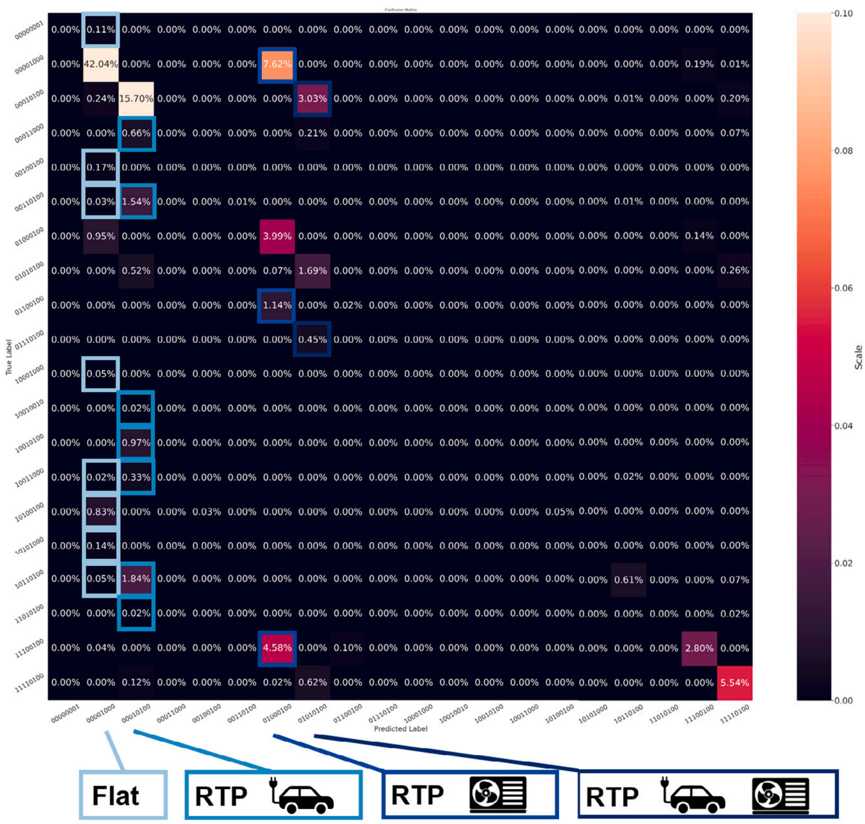

Fig. 12. Exemplary confusion matrix, showing the overclassification of the four most frequent classes.

UK [83,84]. By multiplying the calculated number of inhabitants with the average apartment size per person in London (33 m^2), the living space of each household is determined [85]. Taking the average annual heating demand per square meter of 133 kWh/m^2a into account, the annual heating capacity required is determined [86]. For water heat demand, the average water consumption of 40 liters per person and day multiplied by the energy needed to heat it up to 40 °C [87].

The daily demand for hot water is assumed to be static over the year. The heating demand for space heating needs to be distributed over time. For this, we take advantage of historical, hourly resolved, temperature data from London in 2012 and 2013 [58]. We assume that space heat is only produced when temperatures are below the heating limit with a daily average temperature of 12 °C (in line with Recknagel et al. [66]). This leads to 214 heating days in the first year and 202 heating days in the second year. The space heat demand is then equally distributed over the heating days.

Appendix D. Mobility

For this study, we use mobility data from the German Mobility Panel [68]. It includes detailed driving profiles of private households in Germany in everyday life during an ordinary week. The data collection includes various data of which we use the ID, means of transportation, day of the week, departure time, distance traveled, arrival time and trip purpose. We only consider trips for which a car is used as means of transportation.

From the panel's extensive data collection, a commuter and a non-commuter driving profile is randomly assigned to each electricity consumption profile, which creates two synthetic customers for each consumption profile and enables a comparison of the two characteristics. A driving profile is considered to be a commuter profile if the workplace is visited at least four times a week. We only consider profiles for which the parking time of the car at home is always long enough to recharge the car sufficiently to complete the subsequent trips until the car returns home. Finally, the mobility profile is extended to the two year time frame of the case study, by repeating the driving profiles.

Table 7
Optimal hyperparameter combinations for XGB.

Data input	Learning rate	Min. child weight	Max. depth
Basic	0.1	4	3
Basic + weather + smart meter	0.1	7	6

Table 8
Optimal hyperparameter combinations for ANN.

Data input	Learning rate	Batch size	# units in dense layers
Basic + weather + smart meter	0.001	50	64

Appendix E. Optimal hyperparameters

See Tables 7 and 8.

Appendix F. Confusion matrix

Fig. 12 shows the false classification of smaller classes as majority classes. Each row represents a true label and each column represents a predicted label. The four most frequent classes are labelled.

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