A Data-driven Fairness-based Time of Use Tariff Design

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Analysis

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Abstract

Time of use (TOU) tariffs aim to shape demand, by reducing peak demand and otherwise changing the load shape, which is of heightened relevance as energy supplies come under pressure and transition from fossil fuels to more volatile renewable sources. However, TOU tariffs may carry distributional consequences, such as higher bills for all users/low-income users. With the increasing prospect of steep increases in energy bills in Europe, a fairness-based approach TOU tariff design deserves proper attention by the world's regulatory regimes. A flexible, fairness-based TOU tariff design is proposed, utilizing a 4-step data-driven approach to segment households by income and price responsiveness, followed by potential tariff filtering to simultaneously lower total costs, distribute cost savings progressively and maintain constant utility profitability. The new tariff design approach is demonstrated using the 2009-10 Irish Smart Metering Trial, and produces promising results.

Keywords: Fairness of Distribution, Fairness of Transition, Time of use (TOU), Electricity tariff, Tariff design, Price responsiveness, Income, Cost reduction

Introduction

The benefits of time of use (TOU) tariffs for utilities are well-documented. By charging higher prices during peak hours, TOU can shave peak demand and reduce peak costs [1]. It has been demonstrated that TOU can be used to relieve network congestion and improve transmission and distribution network reliability, thereby easing infrastructural investment requirements for generation capacity and grid upgrade [2]. In addition, by shaping demand, TOU can help balance electricity supply in the short run, for example, in response to forecasting errors or natural volatility in renewable energy [3].

However, studies have found that the change to TOU can create distributional effects, with some users facing lower bills and others facing higher bills [4,5]. In particular, low-income users may face higher bills from such a transition. Low-income users may have limited flexibility in changing the time of use of electricity because their residences are poorly insulated and are unable to retain reasonable temperatures when heating or cooling systems are shut down [6-8]. Tariff structure itself can also play a role. In moving to TOU tariffs, the cost burden shifts from users with flatter usage or non-coincident peaks to those with high coincident peaks, so that high-income users may have lower bills even if they use a lot of electricity because the electricity is used when it is cheap, whereas low-income users may have higher bills because, despite lower base-loads, they use electricity during peak hours when it is expensive [9].

Historically, regulators have attached great importance to the fairness of tariffs. They often favour progressive tariffs, such as increasing block pricing [10,11], and are reluctant to approve any tariffs that they think may impose an extra burden on low-income users, such as simple Ramsey-Boiteux-inspired fixed charges with lower energy charges [12,13]. [1] Experience suggests that regulators use electricity tariffs as an instrument to reduce income inequality.[2] A few studies [15,16] have found that regulators adopt more income redistributive electricity tariffs where greater income inequality can be identified. This concern with fairness

[1] Under certain conditions, Ramsey-Boiteux pricing maximises allocative efficiency when unit prices differ from their marginal cost. Ramsey-Boiteux pricing requires that the price of a good be inversely proportional to its elasticity of demand. In the context of electricity tariffs, this suggests that fixed costs should be recovered from services with inelastic demand (e.g., fixed consumer charges for access) rather than from services with elastic demand (which should be priced close to marginal cost). Simple Ramsey-Boiteux pricing fails to address distributional considerations.

[2] Borenstein and Davis (2012) commented that "the reality is that whenever policymakers can influence prices there is a temptation to use these prices to accomplish distributional goals" [14].

explains why regulators have approached residential TOU tariffs with great caution, despite the systemic cost-reducing benefits [4,17,18].

Previous TOU tariff proposals have paid limited attention to fairness. These proposals have tended to focus on objectives valued by utilities, such as peak reduction, profit maximisation, and cost-reflectivity, but have rarely taken into account the fair allocation of costs between users and utilities and the fair cost distribution amongst users of different income levels. Whilst some tariff proposals have been designed in accordance with bill neutrality, which keeps the total costs for users unchanged [19, 20], the fair cost of allocation between users and utilities, which is vital for peak cost reduction as the cost is mostly captured by utilities as a result of TOU adoption, has been overlooked. Other tariff proposals have attempted to lower the cost for users explicitly through multi-objective optimization [21,22], but treat users as a homogenous group and thereby do not consider the fair cost of distribution among users with different income levels. It is likely that total expenditure for the group decreases but bills for certain sub-groups increase, which will result in unfair cost distribution if these subgroups comprise low-income users.

Accordingly, an important research gap addressed in this study is how to design a TOU tariff that provides a fair cost of allocation between users and utilities and a fair cost of distribution among users with different income levels.

Fairness in Tariff Design

Fairness in tariff design has been studied by welfare economists, behavioural economists, and ethical philosophers. Drawing on this literature, we conceptualise fairness of tariff design in two dimensions, namely, fairness of distribution and fairness of transition.

Fairness of distribution addresses the cost distribution among users of different socio-economic status. This encompasses the theory of "vertical equity" and the concept of "need". In welfare economics, "vertical equity" concerns the treatment of people with different income levels, as opposed to "horizontal equity", which proposes that people of similar income levels should be treated similarly [23, 24]. "Need", according to ethical philosophers, calls for adjustive measures to create equitable outcomes for all members of society, regardless of their socio-economic status. The fulfilment of basic needs, such as access to electricity, has been argued to be a precondition for all other elements of social justice [25]. In the context of tariff design, fairness of distribution implies that low-income users should not be harmed following

the transition to a new tariff plan and should have cost savings no less than those of high-income users.

Fairness of transition addresses the relative change of welfare from the old to new tariff. This draws on the "reference dependence" theory of behavioural economics and the concept of "desert". Kahneman [26] put forward the concept of reference dependence, which states that people evaluate outcomes relative to reference points. The reference points can be the status quo [27] or the expected outcome [28-30]. "Desert" is the ethical condition that someone (the deserver) deserves something by virtue of something (the desert base). For example, a student deserves a good grade by virtue of hard work. In the context of tariff design, fairness of transition has direct implications for users and utilities. For users, a fair transition is one that results in a lower bill relative to their old tariff, the reference point. For utilities, fairness of transition means earning the same level of profits as before the tariff change, since lower profits violate the reference entitlement of utilities, while higher profits derived from raising prices in conditions of excess demand are not considered by consumers to be "deserving" [31-33][3], especially when the company is perceived to be a public service provider [34].[4]

Table 1 summarises the theories that underpin the two dimensions of fairness and their implications on TOU tariff design.

Table 1. Dimensions of Fairness and Implications on TOU Tariff Design

Fairness	**Underlying theories**	**Implications**
Fairness of transition	Desert	Controls on extra profits for utilities should be in place to avoid the perception that utilities unfairly gain from different pricing
	Reference dependency	A large majority of users should be better off in both low-income and high-income user groups after transition
Fairness of distribution	Need/vertical equity	No low-income households should have higher cost after transition
		The benefits received by low-income households should not be lower than high-income households

[3] An example is the strong negative reaction against the surge pricing of Uber during peak demand times.

[4] Private companies in industries such as transportation, telecommunication, and electricity are often perceived by the general public to be public service providers even when they are not [35].

Significance of Fairness-based Tariff Design

Past tariff proposals have failed to give sufficient attention to fairness. Tariff proposals usually aim to pursue objectives valued by utilities, the most cited of which include peak reduction, profit maximisation, and cost-reflectivity (see Supplementary Information 1). However, these proposals either do not achieve a fair allocation of costs between users and utilities (as in the case of bill neutrality, since this does not pass on savings in generation costs to users [19] [20] [36]), or do not take into account the cost distribution across users (as with multi-objective optimization studies, which tend to treat users as a homogeneous group and thus preclude the possibility that low-income subgroups are adversely affected [21] [22] [37]).

A small number of tariff design studies determine TOU prices through game theory or multi-agent modelling. Typically, these first formulate the objective functions for users and utilities.[5] Utilities seek to maximise their profit function while users seek to minimise their cost function. A repeated game then follows where users and utilities take turns to optimise their objectives: utilities by changing tariff prices and users by adjusting consumption levels. The result is an equilibrium where both parties cease to make further changes due to a lack of incentive to do so. Yang et al. [38] documented a multi-stage game between utilities and users for TOU pricing and obtained a Nash equilibrium TOU design. Celebi and Fuller [39] formulated a multi-agent model of an independent system operator, utilities and users, and used variational inequality to determine TOU tariffs that optimise the objectives of all three parties. Guo and Weeks [40] built an agent-based model and determined the day-ahead dynamic TOU tariffs that maximize the expected profit of utilities. However, none of these studies consider the fairness of the tariff: users merely react to the prices set by utilities, which does not guarantee fair cost allocation between users and utilities or fair cost distribution among users.

The consequences of not considering fairness in tariff design can go beyond economics. For example, new tariffs that render vulnerable users unable to afford the adequate cooling or heating of their homes may have adverse health consequences. In one recent randomized control pilot in the U.S., moving to a TOU tariff disproportionately increased bills for households with elderly and disabled occupants and predicted worse health outcomes for households with disabled and ethnic minority occupants [41].

[5] Some studies include regulators as another party in the game.

Table 2. Conventional Tariff Proposals and Limitations

Tariff designs	Methods	Limitations	References
Bill neutrality	Designing tariffs while keeping the total cost for users unchanged	Potentially unfair cost allocation between users and utilities.	[19,20,36]
Multi-objective optimization	Reducing the total cost for users by optimizing competing objective pairs, such as maximizing utilities' profits versus minimizing users' costs.	Overlooks the issue of fair cost distribution among users	[21,22,37]
Game theory/multi-agent modelling/ agent-based modelling	Determining tariff pricing by modelling the interactions between utilities and users.	No guarantee of fair cost allocation between users and utilities or fair cost distribution among users	[38–40]

Significance of Smart User Identification

Smart user identification can be used to identify users who are responsive to price change (responsive users), in order to provide a more objective description of household profiles for investigating the TOU's implications on households of different socio-economic backgrounds, as compared to conventional user identification methods [42]. TOU tariffs are likely to modify the behaviour of a fraction of users more than the whole user population [43]. There is typically a stark contrast in price responsiveness across different households, with only a few responding significantly to price changes [44,45]. By analysing the consumption data from smart meters, smart user identification technology is able to find responsive users non-intrusively and at low cost. Existing studies usually extract indicators for price responsiveness. Supplementary Information 2 summarises these studies. The most frequently used indicator is thermal sensitivity, which is the change of total energy consumption in relation to the change of outside temperature.

The proposed indicators in these studies, however, are limited in scope and their relationships with responsiveness are not empirically justified. For example, thermal sensitivity as the main indicator of responsiveness has attracted much attention in the literature [46-49], but this only reveals consumer behaviour concerning heating and cooling and disregards other easily adjustable behaviour such as dishwashing. Furthermore, high thermal

sensitivity could at best be interpreted as the "potential" for response, which may not materialise unless the consumers have shown such a tendency, and may just reflect poor insulation.

In this article, we depart from the conventional indicator-based method to develop a new smart user identification-based method that is then incorporated into the TOU tariff design.

Results

We apply our methodology to the dataset from the 2009-10 Ireland Smart Metering Trial, running bill and cost simulations on 1,000 users. The resulting three-tier TOU tariff is shown in Table 3. The tariff is consistent with the principles of fairness summarised in Table 1. All low-income households have protected bills, so they cannot be worse off under the new tariff and utility profits are constrained to remain unchanged.

Table 3. Final TOU Tariff

Off-peak price (Euro cents)	**Shoulder price** (Euro cents)	**Peak price** (Euro cents)	**Bill reduction** (Low-income)	**Bill reduction** (High-income)	**Peak shaving**
11.0	14.0	39.0	8.73%	8.63%	35.60%

The tariff significantly reduces bill payments for both the low-income and the high-income user groups. The bill reduction of 8.7% for enrolled users is substantial given this constitutes an equivalent loss in revenue for utilities, which typically have slim profit margins of less than 10% [50, 51]. Importantly, the aggregated demand peak of the enrolled users also experiences a large reduction of 35.6% and the associated cost savings enable utilities to maintain prior profit levels despite the lower revenues.

This can be compared to random enrolment, in which the same proportion of users are enrolled in TOU and flat-rate tariffs but without conditioning on their income level or responsiveness. Under random enrolment, bills are reduced by less than 1% (Figure 1). The proportions of users belonging to each group are specified in Figure 2.

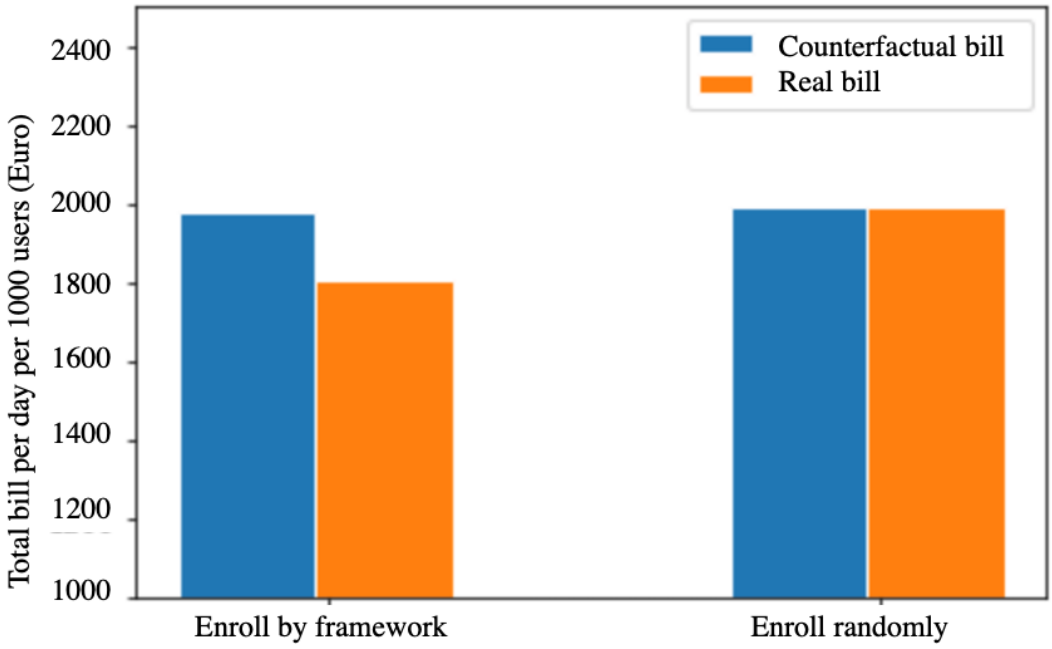


Figure 1. Total Bill Payment

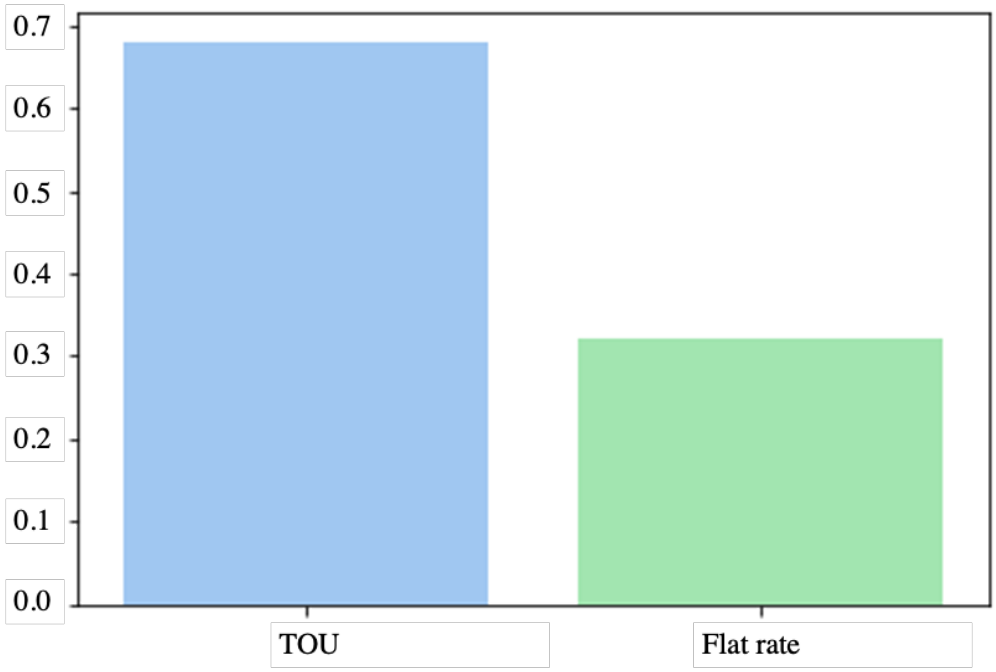


Figure 2. Proportion of Users by TOU and Flat Rate

All low-income users benefit from being enrolled in the TOU tariff, with some experiencing bill reduction as high as 20% relative to the flat rate (Figure 3). In comparison, if they are enrolled randomly into the TOU, over 40% of low-income users experience a bill increase, with some seeing bills higher by as much as 15%, a situation which would

significantly exacerbate energy poverty. Amongst high-income users, only a small fraction, of approximately 10%, have a higher bill after changing to TOU tariffs (Figure 4).

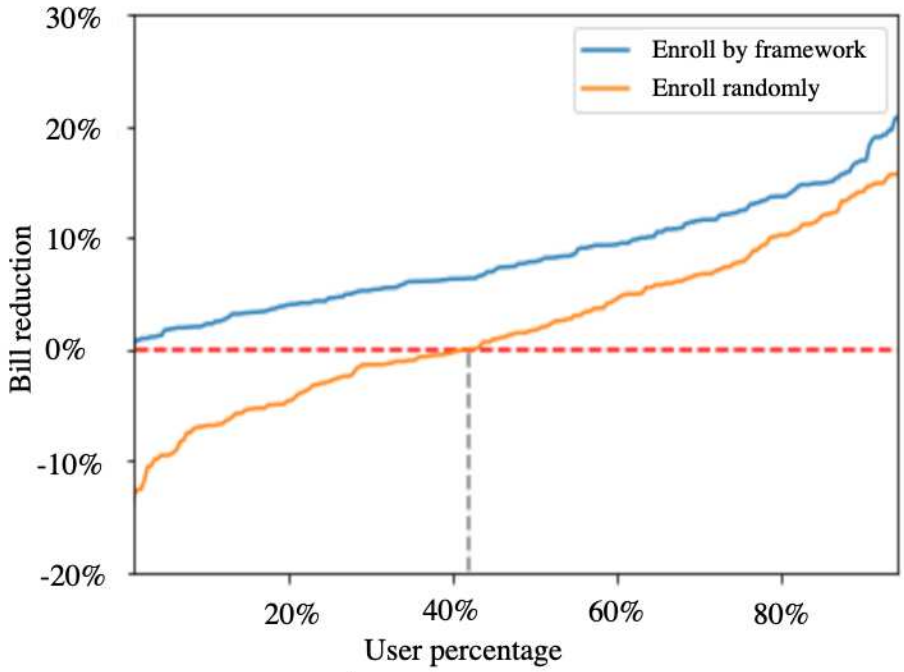


Figure 3. Reduction in Bill Payment by Low-Income Users

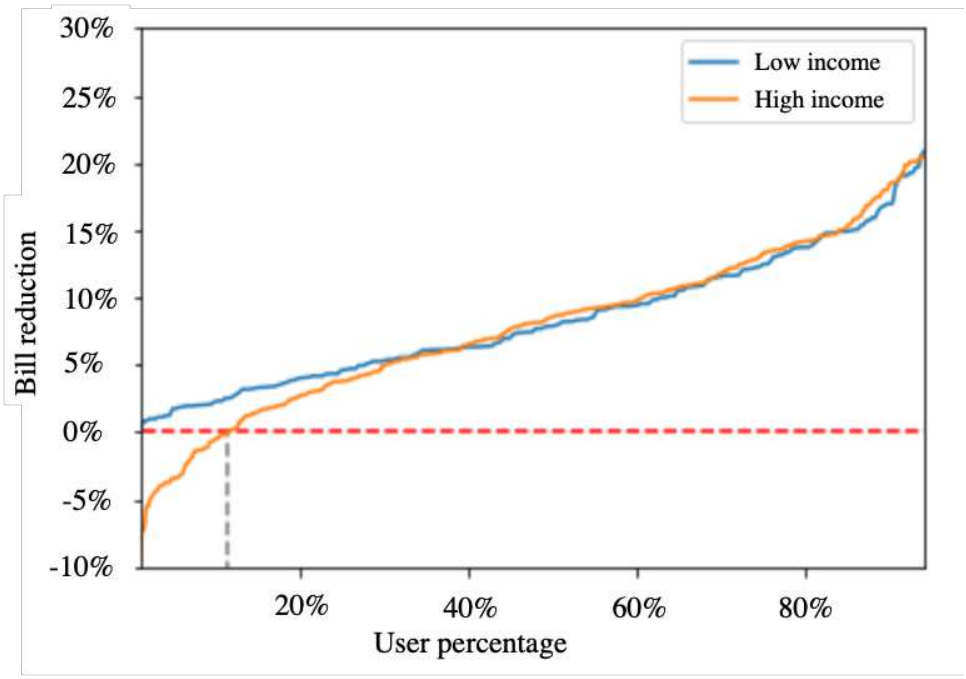


Figure 4. Reduction in Bill Payment by Low-Income and High-Income Users

We have also explored whether it is possible to guarantee that all high-income users have lower costs. The results show that this is not attainable without reducing utilities' profits. This is because high-income users have a much higher peak demand than the low-income users

(Figure 5), so guaranteeing lower costs for each high-income user requires the peak price to be offset with much lower prices at other times, which in turn results in revenue losses for the utilities. However, this loss cannot be fully recovered through the cost saving from lower peak demand, as high-income users are less responsive to price change. The result is that any TOU tariff that guarantees a lower cost for each high-income user will fail to meet the fairness principle of maintaining utilities' profits. As a corollary, this illustrates that the higher peak demand users are cross-subsidized by the lower peak demand users under a flat-rate tariff.

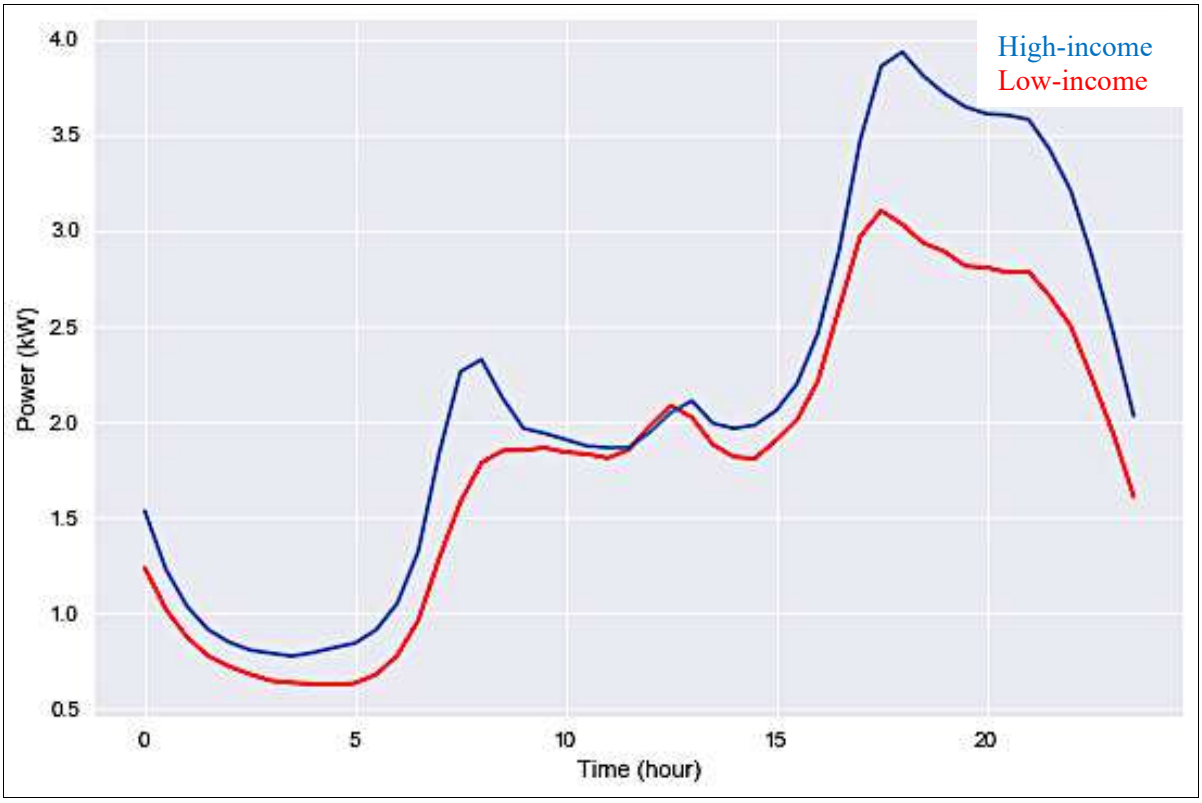


Figure 5. An Average Consumption Profile of High-Income and Low-Income Users

Discussions

Significance of the Study Beyond the TOU Trials

In situations where TOU trials such as the Ireland Smart Metering Trial are not available, alternative methods are needed to identify low-income users and responsive users. In this section we outline an approach on how to achieve this.

For the identification of low-income users, existing studies have already provided methods to infer household income from electricity consumption data with reasonably accurate results. For example, Beckel et al. [52] extracted 22 features (such as consumption level, mean consumption level/maximum consumption level, etc.) from weekly consumption data and

applied four machine learning algorithms to map them to socio-economic properties. Hopf et al. [53] expanded on Beckel et al. [52] by extending the feature set and applying feature filtering. Wang et al. [54] developed a CNN-SVM model,[6] where the CNN is used to automatically extract features from historical consumption data, and SVM is used to classify features into income levels.

For the identification of responsive users, a supervised learning model could be built using data of trial experiments. Figure 6 illustrates the process.

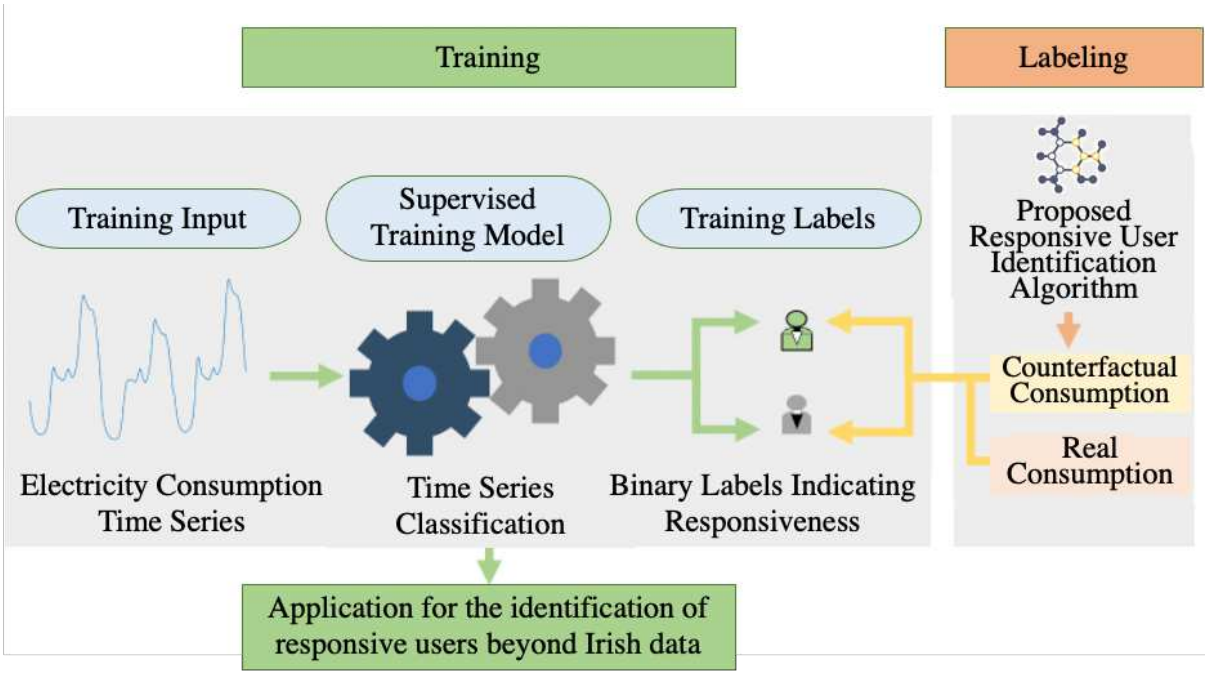


Figure 6. Supervised Learning for Identification of Responsive Users Beyond the Irish Dataset

The training inputs are electricity consumption time series of the treatment group in a TOU trial experiment. The training labels are a binary variable of whether users are responsive, which is obtained through our smart user identification model. The supervised learning model attempts to extract features from training inputs and map them to the training labels. This involves time series classification, an active research field that maps a time series to categorical labels. State-of-the-art algorithms in time series classification include HIVE-COTE, which integrates an ensemble of traditional machine learning algorithms on time series classification

[6] CNN-SVM models combine the Convolutional Neural Networks (CNN) and Support Vector Machines. CNNs are a class of neural networks characterised by convolution layers which extract, and pool features to reproduce them as simpler and smaller patterns. SVMs are a class of supervised learning classification models that aim to identify the hyperplane that maximizes the separation between the different classes.

[55]; InceptionTime, which uses deep learning ensembles inspired by Google Inception [56]; and ROCKET, which uses a large number of randomly parameterised convolution kernels to extract features and ridge regressors to achieve classification [57]. Applying these time series classification algorithms on labelled electricity consumption series may help produce a robust model to predict responsive users for large-scale application.

Limitations of the Study

While this study presents a new methodology for fairness-based TOU tariff design, some limitations remain to be addressed in future follow-up studies:

First, this study models fairness as a number of constraints that the fairness-based tariff must satisfy, rather than as objectives that tariff aims to promote. However, it may be possible to explicitly quantify and maximise fairness, such as Jain's fairness index in the field of telecommunication [58]. In the future, we will aim to create indices of fairness and design tariff that optimises the indices.

Second, the cost functions of electricity transmission and electricity distribution are only crude estimations of real costs based on regulatory documents. In reality, cost estimation is a complicated process that requires sophisticated modelling. Future work could be done to incorporate such cost models into the research.

Third, the three-tier TOU tariff does not determine the timing of peak, shoulder and off-peak windows. Rather these windows are assumed to be known in advance. Future work will integrate the modelling of TOU windows with the modelling of pricing.

Fourth, this study has only designed TOU for half a year. However, tariffs for different seasons/months/days may be needed in order to accommodate changing consumption patterns. For example, [40] introduced a TOU tariff with daily pricing. Future work will expand on current design to include tariffs for each season/month/day.

Method

Data Collection and Pre-processing

We apply our methods to the dataset from the Ireland Smart Metering Trial. This was a 2-year TOU experiment of over 4,000 households with control/treatment groups and a benchmark/test period.[7] The trial set three different prices that each corresponded to different time bands

[7] The dataset is downloadable at https://www.ucd.ie/issda/data/commissionforenergyregulationcer/

during the week. For weekdays, the peak period covered 17:00 to 19:00; the night period covered 23:00 to 08:00; and the day period covered all other times. The dataset also provides a comprehensive survey of household demographics, residential characteristics and electrical appliances.

Table 4. Tariff Pricing of the Ireland Smart Metering Trial[8]

€Cents/kWh

	Benchmark period (Jul. 2009- Dec. 2010)	**Test period** (Jan. 2010-Dec. 2010)		
		Night (23.00-08.00)	**Day** (08.00-17.00 and 19.00-23.00 on weekdays, 17.00-19.00 on weekends and holidays)	**Peak** (17.00-19.00 Monday to Friday, excluding bank holidays)
Control	16.00	16.00		
Tariff A		13.62	15.89	22.70
Tariff B		12.46	15.32	29.51
Tariff C		11.35	14.76	36.32
Tariff D		10.22	14.19	43.13

The consumption data for each household are processed following Figure 7.

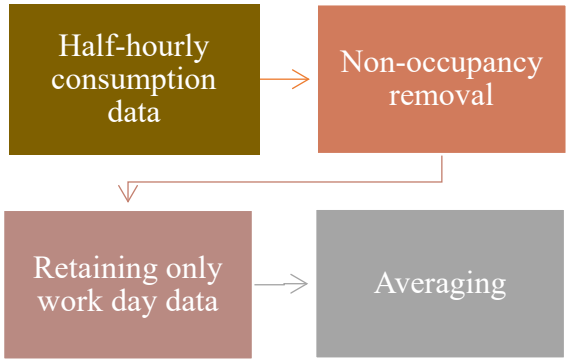


Figure 7. A Data Pre-Processing Flowchart

We define a time period as non-occupied if a user is not at home. Since our study involves studying users' response to price, non-occupancy data would distort the measurement of users' actual response behaviour. We therefore identify any unoccupied periods and remove them from our dataset. Our non-occupancy detection method follows [59] and [60], which determines the state of occupancy by comparing consumption features during the period of

[8] During the benchmark period in October 2009, Electric Ireland introduced a blanket tariff adjustment. However, the price change was meagre at only 0.2 cents/kWh, so we ignore this adjustment.

interest with the inactive period (such as the early hours of the morning). The non-occupancy detection algorithm is provided in Supplementary Information 3.

Due to the disparate consumption pattern of weekends and workdays and the fact that peak demand occurs at workdays, we retain only the workday data. We have also taken the half-year (July-December) average in the years 2009 and 2010 respectively to smooth out volatility.[9]

A Four-step Fairness-based Smart TOU Design Model

We propose a novel four-step filtering model to determine the TOU price, as illustrated in Figure 8 Four-step filtering model. The algorithm iteratively proposes TOU tariffs, applies them based on income and price responsiveness, and removes those that fail to meet the fairness-based principles.

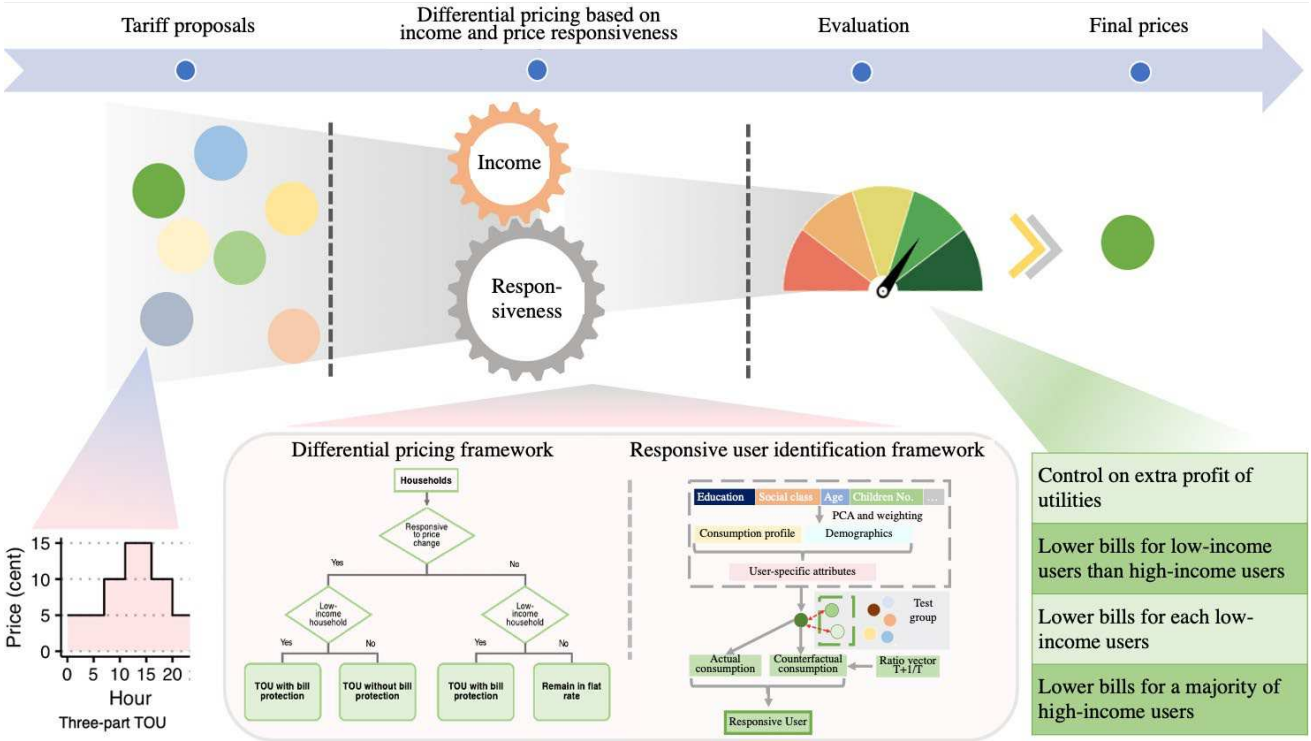


Figure 8. A Four-Step Filtering Model

[9] The reason for half-year averaging rather than full-year averaging is because the time span of the dataset in 2009 only covers a half-year period from July to December. Taking a half-year average produces two consumption profiles for each household during the corresponding period of different years.

Step 1. Tariff Proposal

Tariff proposals are generated. A tariff proposal is defined as any tariff that has TOU features, i.e. a higher price (relative to the flat rate) during peak time and a lower price during off-peak time. We limit tariff proposals to those with a two-tier (one price for peak time and one price for off-peak time) or three-tier structure (one price for peak time, one price for the shoulder time and one price for off-peak time). These two structures are chosen as they are simple for users to understand and avoid high price volatility. Constraints for these TOU proposals are detailed in Supplementary Information 4.

Step 2. Differential Pricing Based on Income and Price Responsiveness

Households are enrolled into TOU tariffs according to Figure 9**Error! Reference source not found.**. Unshaded rhomboids represent branch points at which decisions are made and shaded rounded rectangles represent end points where households are assigned to tariffs. Whether and how households are selected for TOU tariffs depend on two factors: 1) whether they are low-income households, and 2) whether they are responsive to TOUs.

Responsive users are defined as those whose price elasticity at peak time exceeds the median value of elasticities of all users (i.e. those users with the most negative elasticity). Low-income is defined by other demographic variables in Supplementary Information 5.

Based on these two factors, households are placed on the TOU tariff with bill protection, placed on the TOU tariff without bill protection, or remain on the flat rate. "TOU tariff with bill protection" means that the household is enrolled onto the TOU tariff but that their bill is calculated as the lower of the TOU tariff or the flat rate.

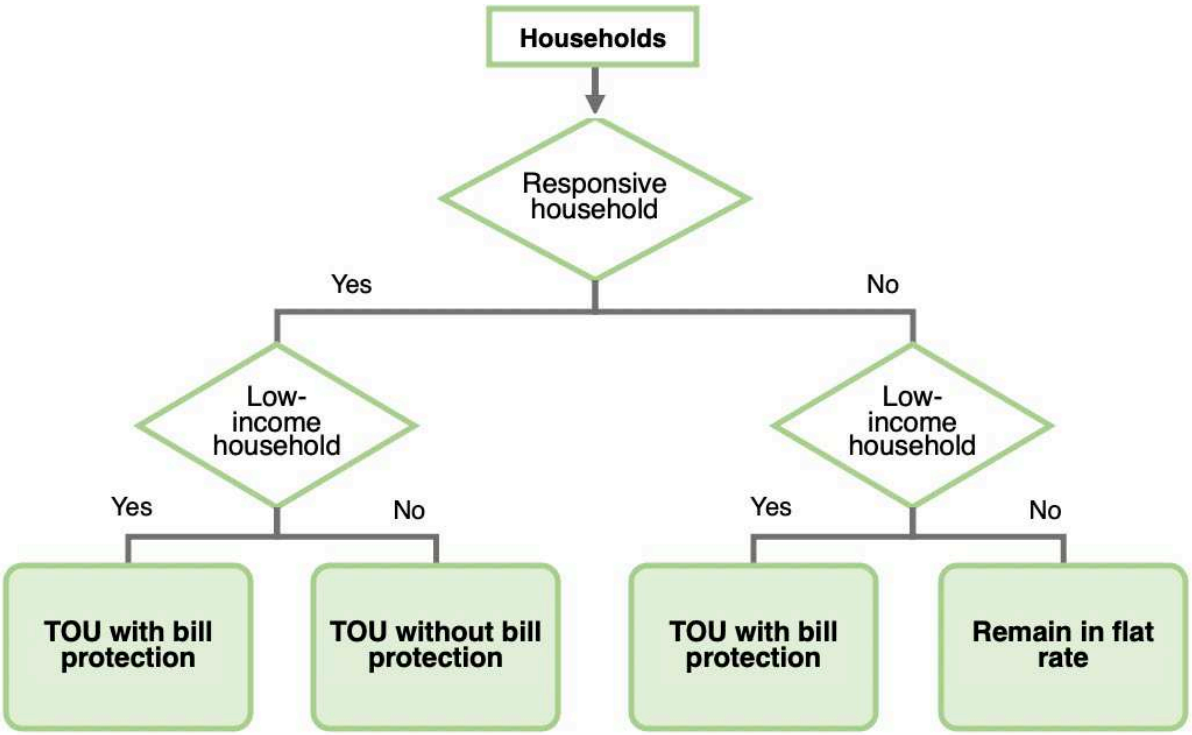


Figure 9. A Framework for User Enrolment

The framework serves three purposes. First, placing responsive households on the TOU tariff helps to shave peak demand and reduce peak costs. Second, it ensures cost savings for low-income households as they are put under bill protection. Third, it affords the best opportunity for high-income users to reduce bill costs, as it only places responsive users on TOU and does not penalize non-responsive high-income users.

Step 3. Evaluation

Each tariff proposal will be evaluated according to fairness as defined in Table 1. Any tariff proposal that fails to pass these constraints will be removed and the process returns to Step 1 with a new tariff proposal. The mathematical formulation of the fairness implications of Table 1 is detailed in Supplementary Information 6.

Simulations for the demand and costs for each individual user and utilities are made based on Equations (2) and (3). Price elasticities are estimated at peak, off-peak and shoulder periods for each member of the treatment groups (Tariff A - Tariff D, as elaborated in Table 4), using the estimated counterfactual and real consumption[10].

Step 4. Final Pricing

[10] Both positive and negative elasticities are treated as the estimated.

The filtering process from Steps 1 to 3 will produce a collection of tariff proposals that satisfy the constraints. The optimal tariff will be selected from the collection that maximises the cost savings for users.

$$\underset{p_{it}}{\operatorname{argmax}}\left(\sum_{1}^{N}\sum_{1}^{T} d'_{it}p_f - \sum_{1}^{N}\sum_{1}^{T} d_{it}p_{it}\right) , \tag{1}$$

where d_{it} is demand for consumer i in period t, p_f is the flat-rate price and p_{it} is the price under the TOU tariff facing consumer i.

General Assumptions:

The following assumptions have been made:

Assumption 1: A user responds to pricing via his own-price elasticity.

Following prior studies [10,11], we assume that a user's response to pricing is governed by his own-price elasticity. [11]

$$\mathrm{D}_{\mathrm{i\cdot t\cdot}c} = D_{\mathrm{i\cdot t\cdot}f} \cdot (\mathrm{P}_{\mathrm{t\cdot c}}/\mathrm{P}_{\mathrm{f}})^{\mathrm{e_{i\cdot t}}}, \tag{2}$$

where:

$\mathrm{e_{i\cdot t}}$ is the price elasticity for user i at time t;

$D_{\mathrm{i\cdot t\cdot}f}$ is the demand for user i at time t under the flat rate;

$D_{\mathrm{i\cdot t\cdot}c}$ is the demand for user i at time t under the new tariff rate;

$\mathrm{P_{t\cdot c}}$ and $\mathrm{P_f}$ are the new tariff price at time t and the flat rate.

Assumption 2: Cost is approximated by the wholesale hourly spot market cost, the transmission cost and the delivery cost.

$$C(t,\ d) = C_{wholesale}(t,\ d) + C_{transmission}(t,\ d) + C_{distribution}(t,\ d), \tag{3}$$

where:

t is the time of the day;

d is the electricity demand;

[11] The own-price elasticity gives the response of demand to the current price, and the assumption here is that demand in any period does not respond to the prices in any other period. This avoids the significant complexity from considering cross-price elasticities. Qualitatively, if demand is generally a substitute across time (i.e., cross-price elasticities are positive), then introducing cross-price elasticity will tend to reduce quantity volatility, since higher peak pricing leads to greater off-peak demand and lower off-peak pricing leads to lower peak demand.

$C_{wholesale}$ is the wholesale cost, obtained from the wholesale spot market transaction record;

$C_{transmission}$ is the transmission cost, approximated from an existing transmission charge placed on a user in a TOU scheme;

$C_{distribtution}$ is the distribution cost, approximated from an existing distribution charge placed on a user in a TOU scheme.

The wholesale cost refers to the relevant average half-hourly wholesale price extracted from the System Marginal Price (SMP)[12] of the single electricity market in 2010 [61], allowing different cost levels for peak, off-peak and baseload to be proxied. The transmission cost and the distribution cost for residential users are difficult to measure as the cost of network usage is not immediately correlated with electricity volume; these are approximated with the regulatory price (4-Rate Time-banded TuoS and DuoS) in 2010 which, at a minimum, reflect the view of the regulators regarding how much residential users should pay for the use of the network [62,63].

Specific Assumptions for Smart User Identification:

The model that estimates the counterfactual consumption rests on the following assumption: Two users have a similar rate of change in electricity consumption from year T to T+1, if they have: 1) a similar electricity consumption pattern (therefore similar consumption behaviour), and, 2) a similar demographic profile. This assumption is based on extensive evidence showing that electricity consumption behaviour is strongly associated with historical consumption patterns and demographics [45, 64–67].

We use data from the control group to implement the smart user identification algorithm. Since a user in the control group faces the same tariff across both years of the study (i.e., 2009 and 2010), the consumption in 2010 would serve the counterfactual consumption should they be applied to the TOU. Therefore, the data from the control group can be used to develop the model for counterfactual consumption.

We further split the control group users (N=695) into a training set, a testing set, and a validation set. Figure 10 illustrates the splitting methodology. The training set and the testing

[12] The SMP is comprised of the shadow price and uplift. The shadow price reflects the marginal cost of the most expensive generator to meet demand. Uplift relates to generator start-up and no-load costs.

set represent 80% of the users in the control group. Both are respectively used for training and determining parameters of the model through a five-fold cross-validation. The validation set represents the remaining 20% of the users in the control group, and is used for validating model accuracy.

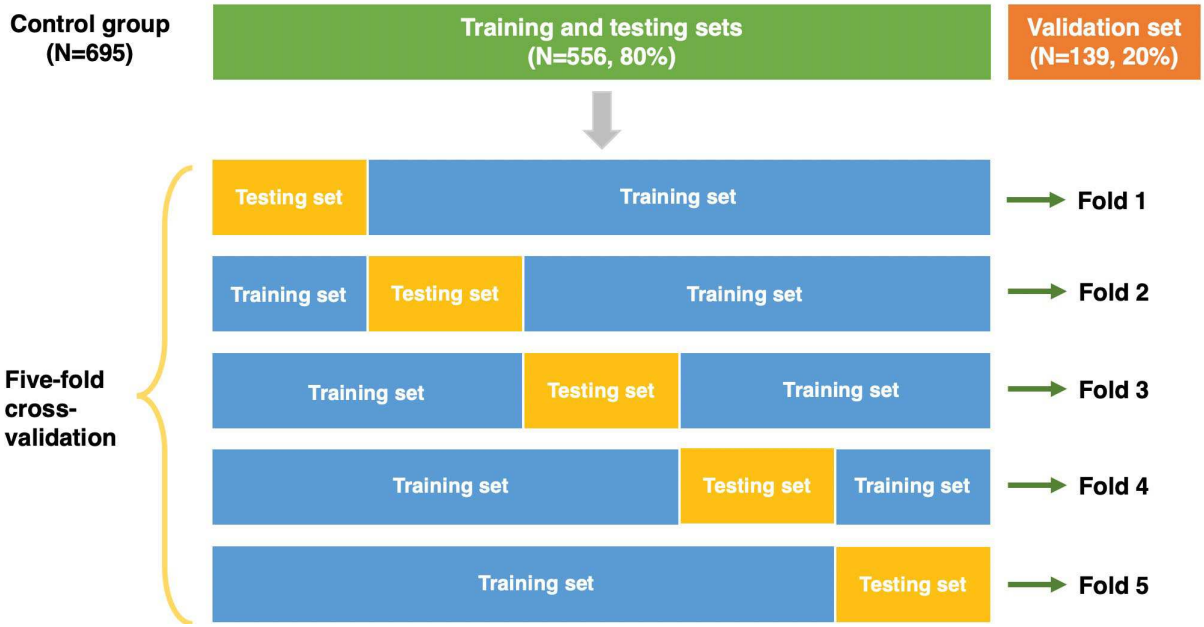
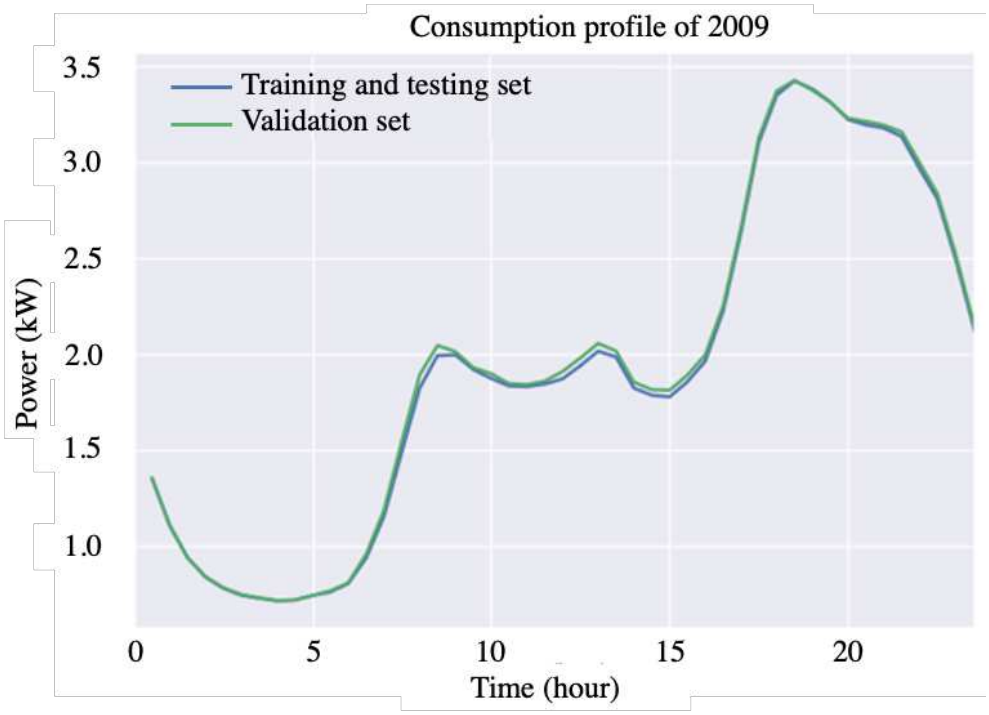
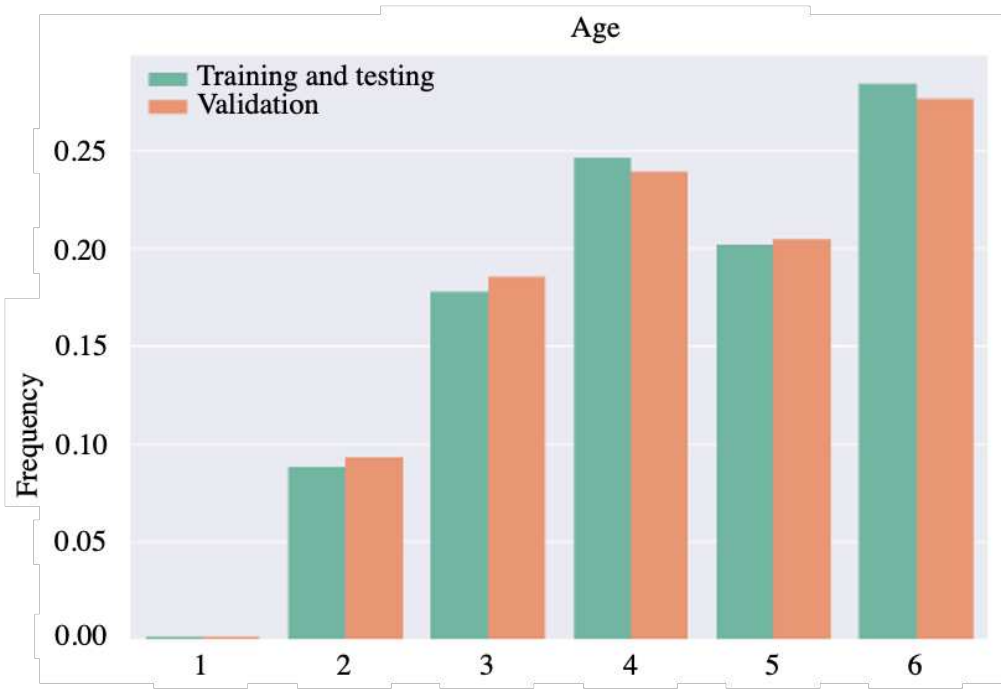
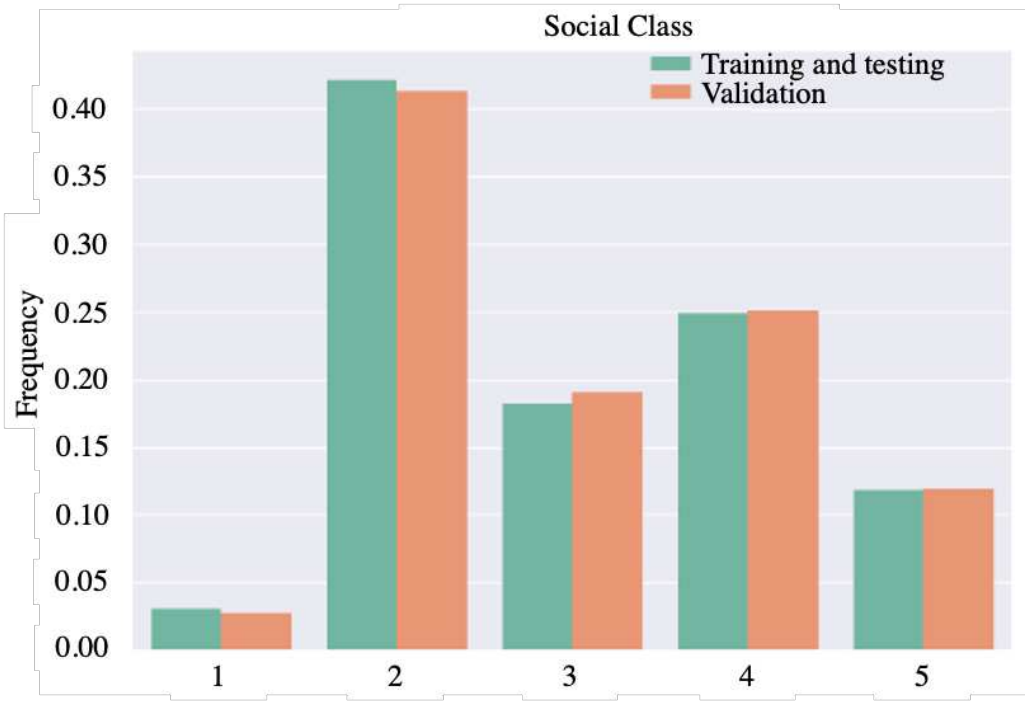


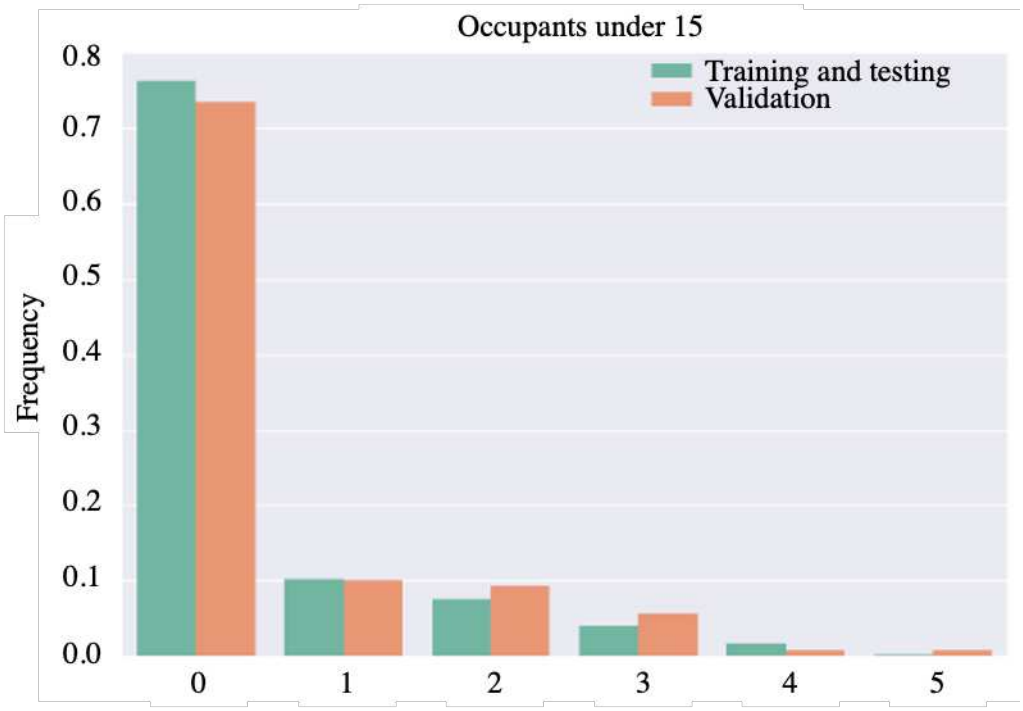
Figure 10. A Splitting Methodology for Users in the Control Group for Training and Testing

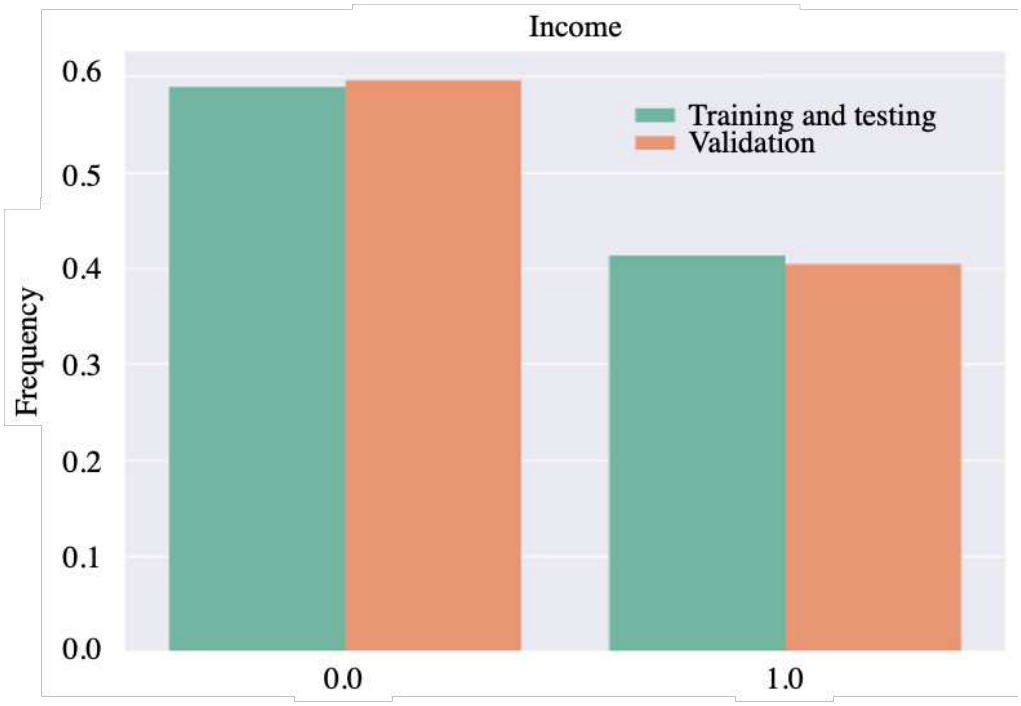
Figure 11 compares the statistics of the training set and the testing set with the validation set (definitions for each variable are detailed in Supplementary Information 5). As shown, there is no significant difference between the training set/the testing set, and the validation set with respect to consumption pattern and demographic.


Consumption profile of 2009
Training and testing set
Validation set
Power (kW)
3.5
3.0
2.5
2.0
1.5
1.0
0
5
10
15
20
Time (hour)


Age
Training and testing
Validation
Frequency
0.25
0.20
0.15
0.10
0.05
0.00
1
2
3
4
5
6


Social Class
Training and testing
Validation
Frequency
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
1
2
3
4
5


Occupants under 15
Training and testing
Validation
Frequency
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
1
2
3
4
5


Income
Training and testing
Validation
Frequency
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.0
1.0


Employment Status
Training and testing
Validation
Frequency
0.4
0.3
0.2
0.1
0.0
1
2
3
4
5
6
7

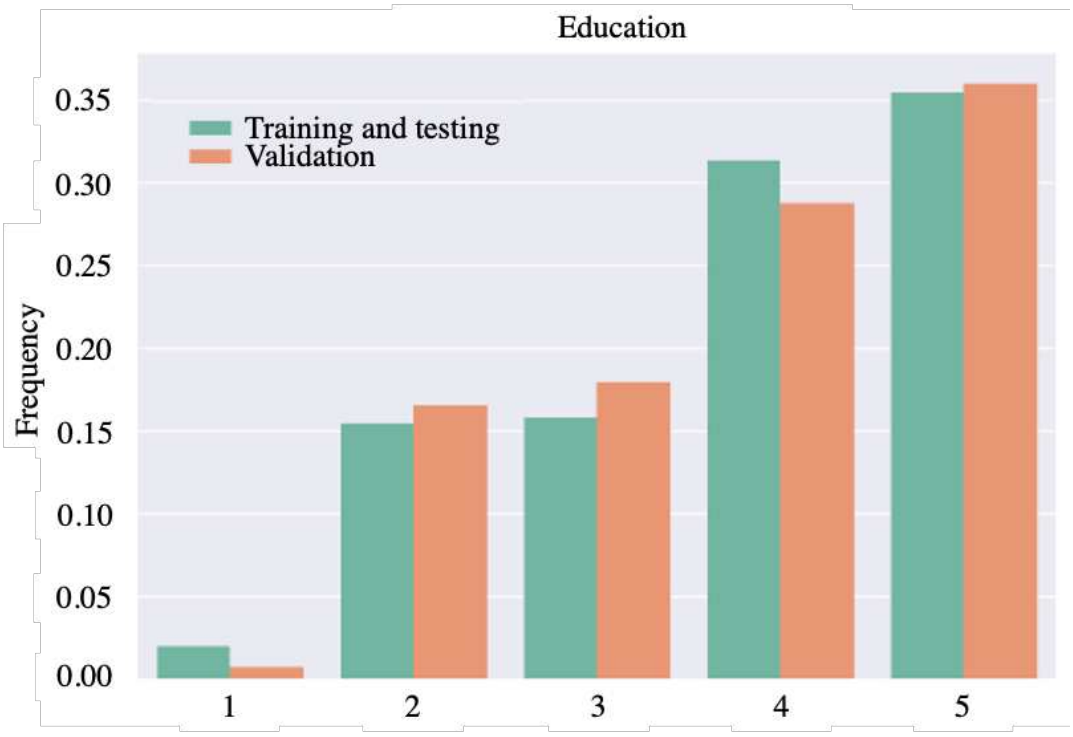


Figure 11. A Comparison of the Consumption Pattern and the Demographics of the Training, Testing, and the Validation Set

A Three-step Counterfactual Estimation Model for Smart User Identification

To identify users who are responsive to price changes so that they can be assigned to the TOU tariff, we develop a new smart user identification method. This comprises 3 steps as shown in Figure 12 and Figure 13.

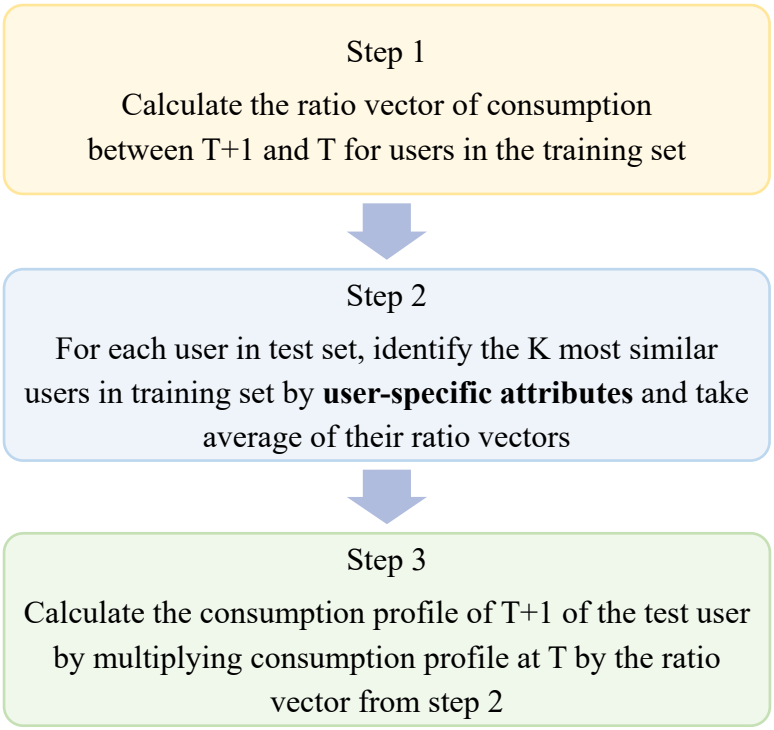


Figure 12. A 3-step Counterfactual Estimation Model

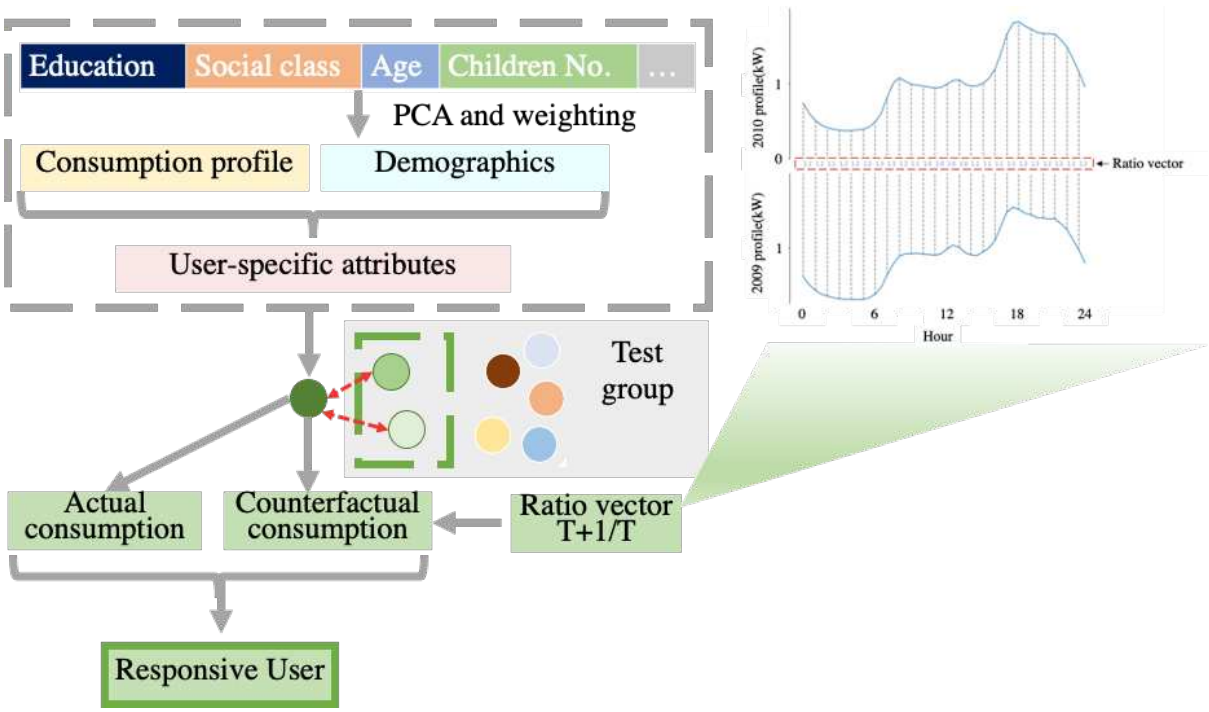


Figure 13. A Framework for Responsive User Identification

Step 1. Calculating the Consumption Ratio Vector

We calculate the ratio vector of consumption between T+1 and T for all users in the training set (Equation (4) and Figure 14). These ratio vectors form a collection of trajectories of consumption change that users may follow if there is no TOU intervention.

$$\text{Ratio Vector}_{\text{i}} = \frac{\text{Consumption Profile 2010 of User } i}{\text{Consumption Profile 2009 of User } i} \tag{4}$$

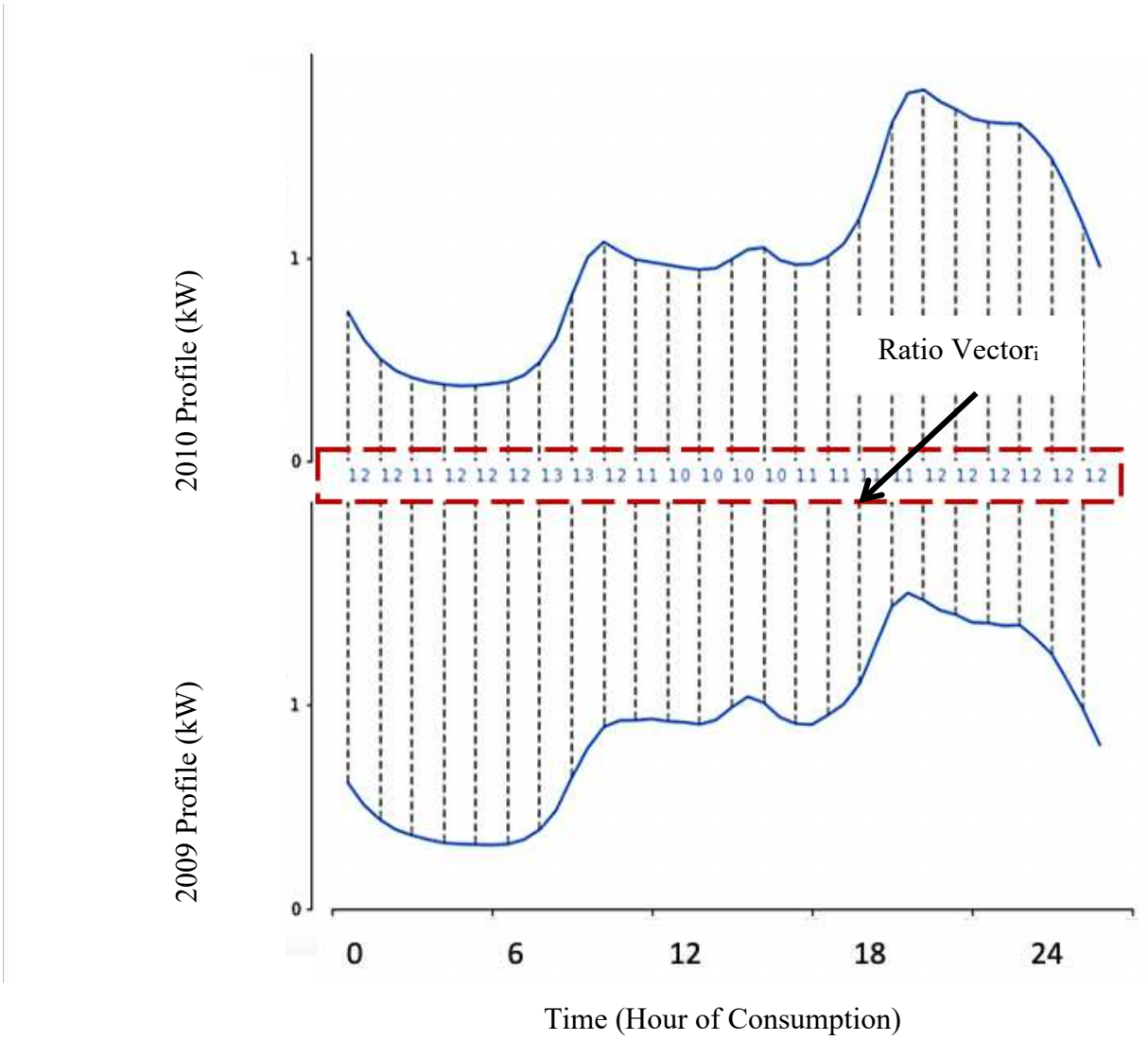


Figure 14. The Ratio Vector of Consumption for All Users in the Training Set

Step 2. Matching Users with the K Most Similar Users

We match the users in the testing set with *k most* similar users in the training set and retrieve the averaged ratio vector. The similarity is defined by the Euclidean distance between user-

specific attributes. User-specific attributes include the consumption profile of the user as well as their demographics (Supplementary Information 5). Since demographics encompass a wide range of factors, Principal Component Analysis (PCA) is first used to uncover underlying factors. The PCA representation of the demographics is then weighted with a parameter *w* and concatenated with the consumption profile of 2009 to form the user-specific attributes. In a similar way to KNN,[13] every user in the testing set finds the *k* most similar users in the control set. The ratio vectors of the *k* selected users are then averaged to return the ratio vector for the users of the testing set. Both parameters *k* and *w* are chosen at the next step by cross-validation with the ones that achieve the highest accuracy.

Step 3. Determining the Counterfactual Consumption Estimate

We calculate the 2010 consumption profile of the users in the testing set by multiplying the 2009 consumption profiles of the users by the average ratio obtained from Step 2. Accuracy is evaluated using R squared. The accuracy for the validation set is above 0.9 for each time step. Performance is consistently better than using prior consumption as our predictor (Figure 15). Such a high level of accuracy is necessary for accurate identification of responsive users, given that TOU on average elicits a demand reduction of less than 10% [68]. It also validates our initial assumption that the rate of change of consumption is driven by the consumption profile and demographics.

[13] KNN, or K-nearest neighbour algorithm, is a machine learning classification method that assigns class membership to an object by a plurality vote of its k closest neighbours or assigns a value to an object by the average of the values of its k closest neighbours.

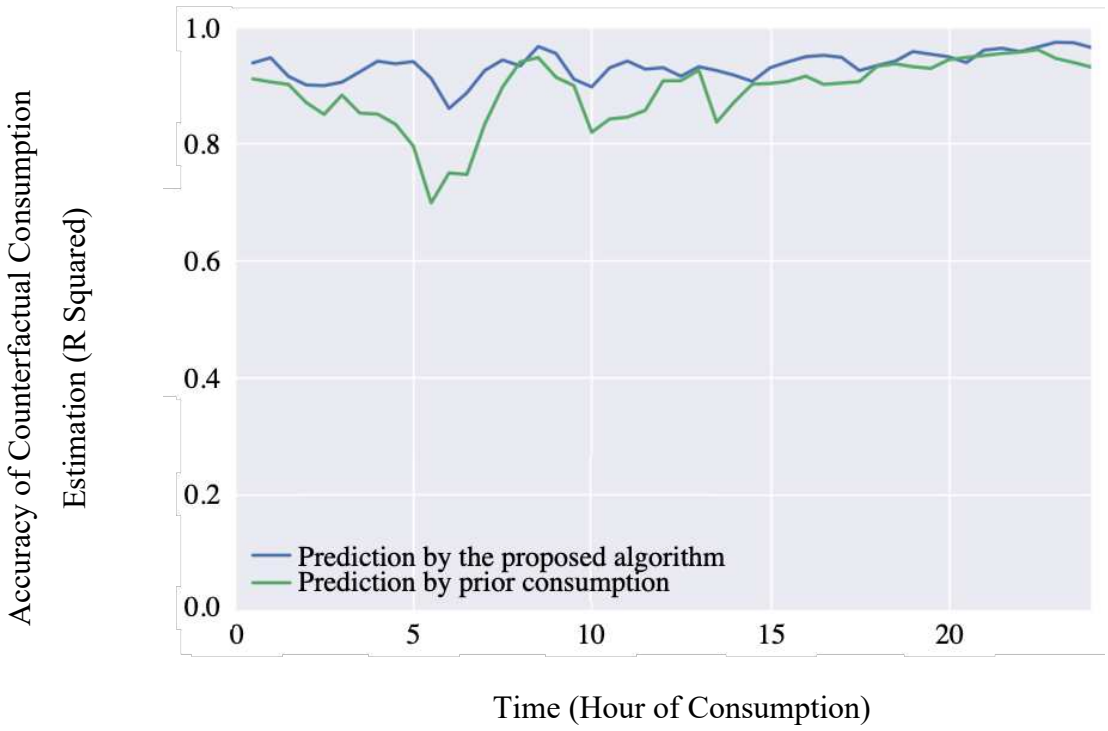


Figure 14. Accuracy of the Counterfactual Consumption Estimation (R Squared)

We have also made a comparison between the peak elasticity estimates by proposed algorithm and prior consumption (Figure 16).

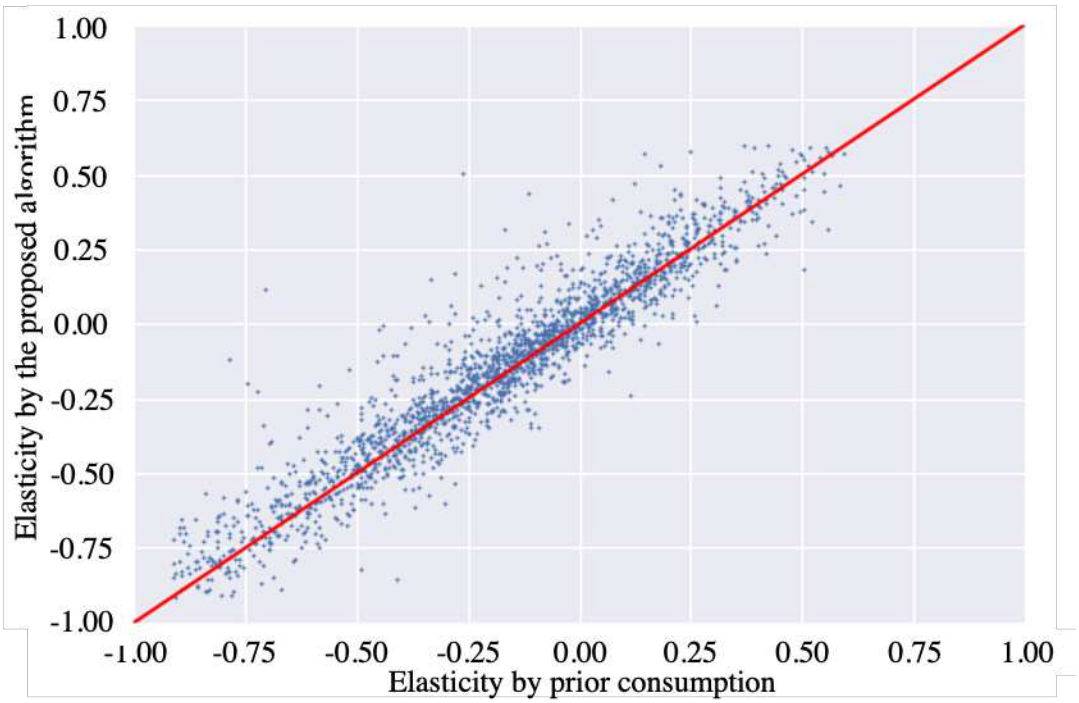


Figure 15. A Comparison of Peak Elasticity by Proposed Algorithm and Prior Consumption

The distribution of estimated elasticities during the peak period is shown in Figure 177. It shows a mean elasticity of -0.27 for low-income users and of -0.18 for high-income users. The estimation is within the short-run elasticity range found in previous studies of between -0.1 and -0.6 [69,70].

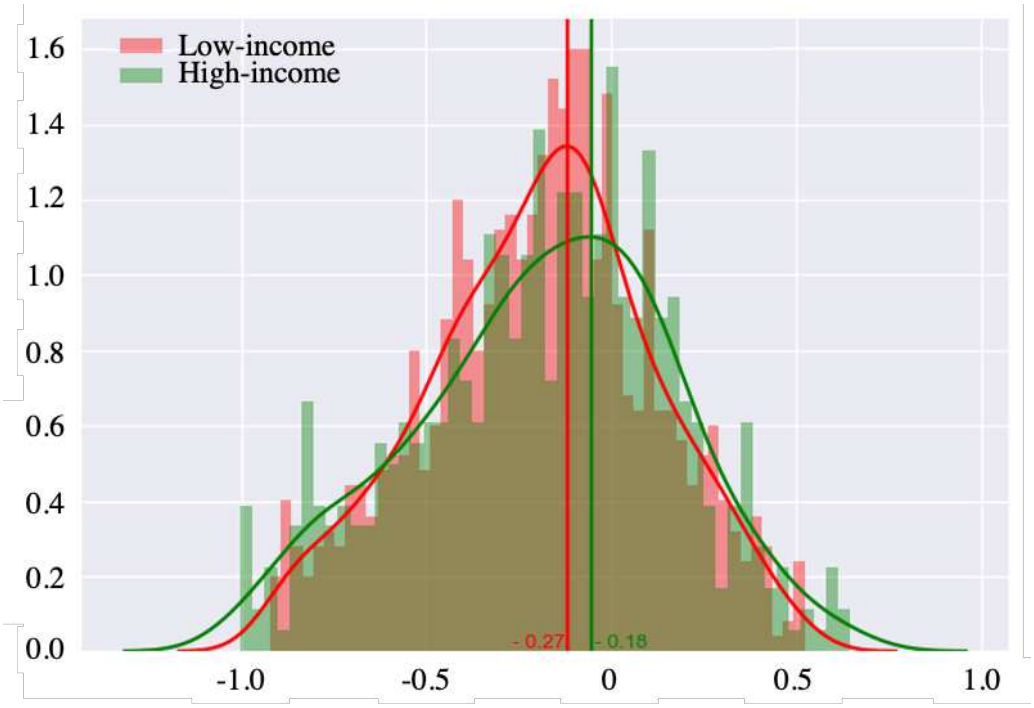


Figure 16. Distribution of Estimated Peak Elasticity

Conclusions

In this study we have developed a new fairness-based TOU tariff approach. Our approach allows the total cost of users to be reduced, principally by reducing peak demand and enabling a corresponding reduction in peak supply and associated cost savings, whilst satisfying explicit fairness criteria, and providing flexibility to define the constraints as deemed appropriate. This is highly relevant to our world context today, particularly against a backdrop of recent world energy development, including steep bill increases in Europe, heightened pressures on energy supplies and the ongoing transitions from fossil fuels to more volatile renewable sources.

We demonstrate our approach by applying this study to data from the Ireland Smart Metering Trial. The tariff reduces total costs of users whilst satisfying explicit fairness criteria. Furthermore, our approach is flexible in allowing allocation constraints to be defined as deemed appropriate. Even under the relatively simple TOU tariff considered, the total bill is reduced by 8.7% compared to less than 1% under random enrolment. At the same time, fairness of transition and fairness of distribution are achieved, so that utility profitability is maintained and cost savings are progressively distributed amongst users, with no low-income users having higher costs and an overall majority of users having lower costs after transition.

Two models have been proposed. Firstly, the four-step filtering model follows an intuitive filtering process to determine the pricing and application of the TOU tariff. The model proposes potential tariffs, applies them to users based on their income level and price responsiveness, eliminates tariffs that fail to meet the fairness constraints, and selects the surviving tariff that maximises cost savings for users. Secondly, a smart user identification model using demographic predictors is constructed to identify users who are responsive to price changes. The model achieves a high degree of accuracy and can be incorporated in broader learning models to classify users in jurisdictions without trial experiments.

Further work remains to be done in endogenizing and extending the model. Firstly, the timing of the peak, shoulder and off-peak windows in the three-tier TOU tariff is treated as exogenous but endogenizing timings should yield superior results. Secondly, the TOU tariff structure could be enriched. In particular, this study is restricted to weekdays and treats these identically, whereas real-world implementation could be improved by a richer treatment, for example reflecting the day of the week, seasonal patterns or potentially even traffic and weather conditions. Thirdly, this analysis provides only a crude exogenous estimate of the cost function; real-world implementation requires much more detailed and sophisticated modelling of the supply side and this could be extended to also consider the joint optimization of supply and

TOU tariff. Lastly, further fairness approaches could be explored, for example to consider scenarios in which household electricity is rationed and other criteria, such as Jain's fairness index from the field of telecommunications [58], could be applied.

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