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Predicting winners and losers under time-of-use tariffs using smart meter data

Y. Kiguchi [a, *], M. Weeks [b], R. Arakawa [c]

[a] Department of Engineering, University of Cambridge, UK
[b] Faculty of Economics and Clare College, University of Cambridge, UK
[c] SMAP ENERGY Limited, UK

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ABSTRACT

Time-of-use electricity tariffs may become more widespread as smart meters are installed across deregulated domestic electricity markets. Time-of-use tariffs and other methods of time-dependant pricing can be mutually beneficial, realising a cost reduction for both energy companies and customers if the customer responds to the price signalling. However, such tariffs are likely to create positive and negative financial outcomes for individuals because of customer engagement and potential peak shifting capacity. Identifying potential reducers or non-reducers beforehand can optimise a time-of-use programme design, in turn maximising the outcome of the programme. This paper provides a statistical model to identify the characteristics of so-called winners and losers - or households that would be better or worse off under a time-of-use tariff - using only ex ante information. The model's accuracy reaches a reliable level using historical electricity load and basic household characteristics. This accuracy can be further improved if online activity data is available - providing justification for digital interaction and gamification in time-of-use programmes. This paper also publishes a new public dataset of 1423 households in Japan, including historical smart meter data, household characteristics and online activity variables during the time-of-use intervention period in 2017 and 2018.

1. Introduction

The total installation of smart meters is expected to rise from 665.1 million in 2017 to more than 1.2 billion by the end of 2024, according to the latest report published by Mackenzie [1]. Asia is and will be the biggest market for smart meters over the next five years, accounting for approximately two-thirds of the global installed base through 2024. China is the key market driver, accounting for more than half of all smart meters installed globally and deploying 476 million smart meters between 2011 and 2017. Japan, the second largest country in this region, deployed 60 million smart meters. In Europe, the smart meter market has a similar rate of adoption as North America, estimated at about 30–40% of all utility customers (Smart Meter Market Report [2]), with an ultimate target of 80% or more according to the 2009 Third Energy Package plan.

Since smart meters record consumption at a frequency of 1 h or less it will be possible for energy suppliers to offer customers tariffs which reflect consumption at a more granular basis. With the increasing penetration of renewable sources of energy generation - which are characterised by higher levels of variability time-based electricity pricing is even more important as a means of facilitating their integration (De Jonghe et al. [3]). The advantages of smart meters for local grids, such as lowering capacity in the distribution network and gathering transmission network data, are also recognised (Depuru et al. [4]). The importance of this "smart" grid has been emphasised by Mathiesen et al. [5] for making a way to a future with 100% renewable energy and transport solutions. In Mathiesen and Lund [6], electric vehicles are identified as the most promising transportation technology and users with flexible demand such as electric vehicles would be more likely to benefit from time-varying electricity prices. Mehrjerdi and Hemmati [7] suggested that optimal dispatching and adjusting of the loads through their proposed demand response program can efficiently harvest the maximum possible energy of the intermittent renewable generation sources.

Many studies have confirmed that TOU tariffs represent a promising demand-side management (DSM) programme for the

* Corresponding author.
E-mail address: yoheikiguchi@gmail.com (Y. Kiguchi).

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Nomenclature

τ	Discrete time slot index in a day
i	Household index
$\overline{C}^{d}_{\tau,i}$	Average half-hourly consumption of household i at time stamp τ during the TOU period
$\overline{C}^{p}_{\tau,i}$	Average half-hourly consumption of household i at time stamp τ during the pre-TOU period
n_p	Number of time indices contained in the peak period
$\tilde{R}_i$	Percentage change in peak electricity usage for household i over the period spanned by the TOU trial against the baseline
$\tilde{R}_c$	Average percentage change against the baseline for households in the control group (C)
R_i	Peak reduction for individual household i
k	Constant threshold
$S_{k,i}$	Flag variable indicating whether household i is a winner in the TOU program given a threshold k %
$\hat{R}_i$	Predicted R_i
$\hat{S}_{k,i}$	Predicted $S_{k,i}$
TP	True positive
TN	True negative
FP	False positive
FN	False negative
mcc	Matthews Correlation Coefficient
RF	Random Forest

residential sector given that it provides more certain financial incentive to customers relative to other DSM programmes such as real-time pricing (Darby and Pisica [8]). A survey in the United Kingdom (The Brattle Group [9]) also confirmed that TOU tariffs are more popular than any other type of time-variable price incentive. 26% of customers indicated that they would switch to a TOU tariff if available. The benefit of TOU tariffs was also empirically demonstrated through the customer-led network revolution load and generation monitoring trials in the UK (Wardle et al. [10]). Another large-scale longitudinal study in Italy (Torriti [11]) also confirmed that TOU tariffs bring about higher average electricity consumption and lower payments by consumers. In total, TOU tariffs have been shown as a successful DSM tool given that these studies observe consumers changing the timing of demand based on a given tariff structure.

The benefits from customer demand response under a TOU tariff may provide potential savings for both energy suppliers and consumers. The European Commission estimates access to dynamic electricity price contracts could generate savings of \euro 309 per metering point distributed amongst consumers, suppliers, and distribution system operators (European Commission [12]). Similarly, the UK gas and electricity regulator Ofgem published a report on the distributional impact of TOU tariffs, highlighting that the average customer facing a £615 annual bill under a flat tariff would save on average £8 (1.3%) under a static TOU tariff (a tariff with different rates during different fixed time periods (Ofgem [13])). A study in the United States estimated that a 5% reduction in peak demand has the potential to provide savings of USD 35 billion in generation, transmission, and distribution costs over a 20-year period (Faruqui et al. [14]).

2. Motivation

Energy suppliers widely have introduced TOU tariffs to their consumers, and there has been previous work on optimal TOU tariffs design. For example, a dynamic multi-objective TOU tariff optimisation incorporating daily and seasonal features of load demand has been proposed by Hu et al. [15], where different indexes, such as electricity cost and user satisfaction, were used for optimisation. The results showed that an optimised seasonal TOU tariff can help in reducing energy bills and improving the satisfaction of users. Likewise, Samadi et al. [16] introduced a multi-layer multi-objective power consumption optimisation model with TOU tariffs that takes into account user experience and comfort. A clustered sequential management method is used to schedule appliances and enhance the user's comfort level.

The proposed work in this paper departs from previous studies in terms of modelling potential outcomes of individual consumers under a TOU tariff using smart meter data and other ex ante information. This model is important given that in practice, energy retailers need to obtain explicit consent from customers to switch energy contracts to a TOU tariff. In addition, despite the benefit of implementation of TOU tariffs at a national level, TOU tariffs are likely to create both winners and losers at an individual level. For example, TOU tariffs can be disadvantageous if a consumer does not (or cannot) shift load in the peak time, and as a result faces an increase in the electricity bill. In this regard, energy suppliers and regulators considering the design of a specific intervention are interested in the ex ante identification of characteristics of individuals who would either benefit or be disadvantaged following the introduction of the policy.

Ofgem [13]'s assessment found that there are households in all groups (including vulnerable groups) that would be subject to increased bills under a TOU tariff. For example, White and Sintov [17] noted that the elderly and those with disabilities with limited flexibility of electricity consumption around peak periods could face greater increases in electricity bills under specific TOU tariffs. Therefore, demand-side measures should be carefully targeted rather than 'one size fits all' and policymakers and energy companies need to remain vigilant to counteract adverse TOU impacts.

This work identifies the characteristics of households who are able to reduce peak load to achieve bill reduction ("winners"), and those households who are not able to reduce peak load and face a bill increase ("losers") using only ex ante information. The reliable identification of the characteristics of potential winners and losers prior to the introduction of TOU tariffs, ensures a better match between tariffs and customers. Three research gaps have been identified to address the aforementioned problem.

First, although prediction-based machine learning methods are promising to inform decision making around the design of a TOU programme (See Kleinberg et al. [18]), the prediction of winners and losers is still not being well addressed. This is because many factors (not only electricity behaviour but other social factors) need to be considered for the model development. For instance, the degree to which TOU tariffs can be fully enforced is affected by considerations such as technical constraints and the willingness of the customer to adapt to the tariff signal (Cousins et al. [19]). Any introduced tariff plan may fail if it does not take account of the customer's point of view (Eskom [20]). A forecasting model factoring in different price responsiveness for each set of customer characteristics is required for raising awareness and incentivising behavioural change to flatten the demand curve and boost bill savings.

A means of enhancing the outcome of the demand side measures is also important. This paper examines the emerging concept of "gamification", which has the potential to improve customer adaptation in a TOU trial with a marginal financial cost. Gamification explores the characteristics of an immersive environment that motivates and engages consumers by using game design elements (Deterding et al. [21]). Gamification-based solutions have been shown to improve the interest of residential consumers in energy systems by addressing a wide variety of customer motivations, including social, environmental and economic motivations (Seaborn and Fels [22]). Based on this, this paper examines how the use of gamification in a TOU trial enhances user engagement.

Lastly, the availability of a publicly available historical consumption dataset (containing DSM trial) is limited given the reluctance of energy companies to release their smart meter data due to security and privacy concerns. The currently available public TOU or DSM datasets are relatively old (with the most recent being from 2014) and customer electricity consumption behaviour can change from year to year. For example, the Low Carbon London (Schofield et al. [23]) dataset collected dynamic TOU readings in 2013 and the Pecan Street TOU dataset has measurements from 2013 to 2014 (Pecan Street Inc [24]). Likewise, the Ausgrid Resident dataset has PV generation readings for domestic power usage according to an inclining block rate or TOU, and controllable load from the year 2010–2013 (Ratnam et al. [25]). The Australian government also released a DSM Smart Grid Smart City dataset, which included readings for seasonal TOU, dynamic peak pricing plan, and rebates for interruptible load for the years from 2010 to 2014 (Australian Government [26]). Furthermore, it can be observed that the available datasets are from EU nations, Australia or US. Therefore, to the best of the authors' knowledge, there is currently no publicly available TOU dataset in Asia. This research work is the first and most recent (from 2017 to 2018) to release TOU public dataset in Asia based on the trials conducted in Tokyo, Japan.

This paper makes the following contributions:

1. A model to *predict* the characteristics of households who will benefit or lose under a TOU tariff using smart meter data and other ex ante information.
2. An examination of the role of gamification in enhancing user engagement with a TOU programme provides insight in designing the programme for favourable outcome for energy companies at low cost.
3. As a side contribution, the dataset used in this paper including historical smart meter data, household characteristics and online activity is made available to promote future research. It is expected that both academic and industrial researchers can utilise the dataset for studying the effects of TOU programme and developing data-driven models.

The remainder of this paper is organised as follows. Section 3 examines the existing research relevant to this field, specifically by identifying studies in the drivers of energy price behaviour, user engagement, and existing trial data. Section 4 outlines how the trial was structured and details the notable components. Section 5 defines the methodological approach to developing and testing the statistical model, and section 6 details the results of these models. Section 4.4 introduces the public dataset created as a result of this trial and gives details on how it may be accessed. Finally, Section 7 summarises the findings and offers commentary for future work.

3. Literature review

There is not a standardised approach in the existing literature to evaluate DSM potential. The three identified research gaps are examined further reviewing relevant academic works in this section: drivers for electricity price responsiveness, user engagement, and availability of public data.

3.1. Drivers for individual electricity price responsiveness

It is generally believed that smart meter data is likely to generate benefits for both consumers, retailers and distribution network operators. Wang et al. [27] showed that degree of the individual potential demand response are graded into several subsets by introducing a demand response evaluation index system. In order for models to identify subsets of the population who are likely to either benefit or be disadvantaged by TOU tariffs, historical consumption data can be supplemented with other data sources. A number of studies have examined the relationship between demand response subsequent to the introduction of TOU tariff and household characteristics. A study of 1300 California households showed that price responsiveness is not observed in all households with a skewed distribution of price elasticity (Reiss and White [28]). O'Neill and Weeks [29] utilised a modelling framework that captured the heterogeneous causal effects of a TOU pricing scheme in terms of differences in demand response. They examined the heterogeneity in household variables across quartiles of estimated demand response and they found reasonable associations with covariates; for example, households that are younger, more educated, and that consume more electricity are predicted to respond more to a new pricing scheme. Guo et al. [30] concluded that demographic and residential characteristics, psychological factors, historical electricity consumption and appliance ownership are significant drivers that determine electricity price responsiveness. Yilmaz et al. [31] surveyed 622 homes to quantify their interest in price-based and direct load control demand response programs based upon their household and socio-demographic characteristics. The results demonstrated that employment, tenure, education, and household type affected the individual user's preference.

Variability in individual load profiles is a key measure for evaluating the potential of DSM since the segment of customers who have a constantly high level of consumption and low-variability during the peak time is thought to be a good target for a DSM programme (Kwac et al. [32]). A state transition matrix obtained by a large data set of load curves was used in (Wang et al. [33]) to calculate the entropy of users, which quantifies variability in usage pattern. The authors found out that for price-based DSM such as TOU, higher entropy users with higher variability and power usage are more appropriate, as their versatility allows them to change their load per electricity price change. On the other hand, lower entropy users' with less variable consumption data is easy to predict and more suitable for direct load control and other incentive-based DSM programs. Using quarter-hourly electricity consumption data, Kwac et al. [34] developed statistical techniques through the measure of variability to identify small and large customer segments that can yield measurable results and high returns for energy programmes. It was discovered that an individual-level energy consumption forecast would be easier for stable customers having less variable load profiles as compared to unstable customers exhibiting highly variable load patterns. Furthermore, the increase in the size of load clusters also considerably reduced the variability in the data.

Appliances such as heating, ventilation and air conditioning (HVAC) have great potential for DSM. The sensitivity of electricity consumption to outdoor air temperature is another effective evaluation criterion to examine the relationship of energy consumption and price responsiveness. Cao et al. [35] developed a model for estimating the average consumption per meter, using clustering methods on load consumption data with a focus on using peak consumption occurrence to segment consumers. Albert and Rajagopal [36] proposed a ranking method for assessing a consumer's viability for a thermal demand response - or energy consumption attributed to HVAC use - where the DSM potential was evaluated using temperature sensitivity and occupancy. Afzalan and Jazizadeh [37] added characterisation schemes for resultant clustered load shapes, with the aim of facilitating information retrieval by assigning cluster load shapes with specific semantic attributes and effectively translating the underlying behavioural actions. Their characterisation scheme extracts descriptive features from load shapes to explain their temporal pattern.

3.2. User engagement

User engagement can be enhanced not only by tariff pricing (Campillo et al. [38]) but also by gamification. Gamification - the trend of employing game mechanisms and techniques in non-game contexts (Deterding et al. [39]) - has dramatically increased in recent years and can be viewed as a new paradigm for enhancing online user engagement. Gamification rewards can be broadly categorised as monetary, status, and achievement rewards (Kankanhalli et al. [40]). Popular design elements of a gamified application includes points, leader boards, rankings, virtual badges, and level status. Empirical studies on gamification (Hamari et al. [41]) have identified the importance of feedback based on motivational messages. Recent successful examples of gamification in other fields are Foursquare and Nike+ (Deterding et al. [21]), which achieve high engagement from customers without monetary rewards.

Engagement with DSM programmes, however, have typically encountered several significant obstacles. Firstly, the majority of customers have only experienced a flat rate for electricity and therefore, an awareness of the significant variation in the intra-day wholesale price of electricity is generally not widely known. Communicating this effectively will have implications to the success of recruitment to the programme and its eventual outcome. Second, based upon extensive literature reviews (see Luthra et al. [42]) and validated with expert opinions from academia and industry, the lack of customer engagement - or initial interest that wanes over time - has been identified as a key obstacle. Programmes must therefore anticipate these issues and engage accordingly, seeking the deeper drivers of energy consumption.

The engagement metrics in a game-enhanced DSM platforms may include the average time of DSM tool usage/user group, an average number of consumers who signed in the DSM tool every DSM-event/month/week, the implemented DSM actions ratio, accepted DSM requests ratio, digital engagement metrics with related DSM data, reliability and flexibility parameters of DSM methods, and psychographic and demographics consumer profiles (See for example, Lampropoulos et al. [43].). As an example, Zehir et al. [44] analysed the engagement of DSM program participants by grouping them into rare and active users according to their gamified DSM platform use frequency. Similarly, Fijnheer and Van Oostendorp [45] monitored the power consumption flexibility and behaviour of consumers by tracking the frequency of the participant's sign-ins and how long he/she is engaged. A study conducted by Schofield et al. [46] utilised a measure of an engagement based upon the distribution of the subsequent annual bills, and using the percentile in which the actual bill occurred as a proxy for engagement.

Gamification appears to be of value within the domain of energy consumption, conservation and efficiency, with some evidence of positive influence found for behaviour and the user experience (Johnson et al. [47]). Paone and Bacher concluded that behavioural feedback (providing building occupants with information regarding their historical and current energy consumption) is an effective means for influencing occupants, with gamification presented as a new opportunity to induce behavioural change (Paone and Bacher [48]). Senbel et al. found that participants in an energy conservation campaign were motivated by the actions and stories of their friends and did not pay attention to the actions or competition scores of strangers (Senbel et al. [49]). These findings suggest that employing mechanisms for showcasing the behaviour of peers may be effective in increasing engagement and in shifting long-term energy consumption.

3.3. Importance of public dataset

Smart meter data collected by conducting the DSM trials offer utilities the chance to manage the energy consumption of individual customers even out of thousands of them. The utilities can test new DSM programs and compare them with the old ones (Ludwig et al. [50]). However, despite the emerging awareness of the importance of DSM, the availability of a publicly available historical consumption dataset, including customer behavioural changes due to a TOU tariff intervention, is very limited. In Wang et al. [51]'s review, only a dozen sources of open data are available given the reluctance of energy suppliers to release their smart meter data due to security and privacy concerns. In many cases, datasets from 4232 households in Dublin, Ireland (Commission for Energy Regulation [52]), 5567 households in London, United Kingdom (Schofield et al. [53]), 40 households in Austin, Texas (US) (Smith [54]) are repetitively used in many papers. There are also researchers who are testing various frameworks and algorithms using such smart meter data but they don't publish their datasets (Ashok [55]) and some are producing the data artificially (Li et al. [56]). However, reference real-world data sets play an important role in making research more comparable and useable.

There is significant evidence that publicly available datasets have spurred previous applications in machine learning and data mining. For example, many early successes in natural language processing were spawned by the now-classic Wall Street Journal corpus (Marcus et al. [57]), and image recognition research has been aided by common benchmark datasets such as MNIST (Modified National Institute of Standards and Technology database) digit recognition (LeCun [58]), CalTech 101 (Fei-Fei et al. [59]), and the PASCAL challenge (Everingham et al. [60]). Wagner et al. [61] pointed out the scarcity of publicly available data in the energy disaggregation field, and created a public data set to support this research.[1]

A wider range of public data sets related to a TOU tariff intervention would enable further examination in this field. This paper addresses this issue by publishing the dataset of a TOU trial result for the future academic research.

4. Time-of-use trial

Energy market reform was implemented in Japan from 2016, where the electricity market was deregulated and competition was introduced (Shinkawa [62]). Japan is the fourth largest market in electricity consumption after China, United States and India (according to the CIA [63]), and the largest single deregulated electricity market.

The deregulation of the electricity market promotes competition, with the market share of new entrants serving 11.7% of total energy demand in July 2017. Japan also has one of the highest rates of smart meter penetration in the world, with 60 million electric smart meters deployed in 2018. The data from smart meters is also live-streamed to energy suppliers, making the utilisation of the smart meter data technically feasible. Moreover, products and

[1] The energy disaggregation field is focused on detecting appliance-level usage from a household energy consumption profile and this dataset is referred to as REDD - Reference Energy Disaggregation Data Set.

Table 1
Users on TOU/Flat tariff.

Period	Start date	End date	Number of Days	TOU users	non-TOU users
Pre-TOU period	1 June 2018	30 June 2018	30	Flat tariff	Flat tariff
TOU period	1 July 2018	30 September 2018	92	TOU tariff	Flat tariff

services - like TOU tariff - are welcomed by energy suppliers as a means to differentiate their offers in the competitive market.

Looop Inc., one of the new entrants in Japan, introduced a TOU tariff for customers in Tokyo. The CAMSL dataset was generated based upon the introduction of a TOU tariff trial in 2018 (Looop TOU campaign [64]) by Looop Inc. and SMAP Energy.[2]

1023 households in Tokyo (TOU users) voluntarily participated in this trial. During the programme, volunteer users were assigned to a TOU tariff during July 2018 to September 2018 (92 days), the remainder were assigned to a flat tariff (see Table 1). All TOU users had access to their historical energy consumption charts via a web application and were also provided with daily email notifications indicating any peak reduction in consumption against an individual baseline which was set based on June 2018 consumption (see Section 4.2). A limited amount of demographic information - specifically household type and number of residents - was collected via a questionnaire.

Several key features explored in this trial are explained in the following sections. The first is the structure of the TOU tariff, which allows the price of electricity to vary according to the time of the day and the day of the week. The second is the web application, which provides personalised feedback regarding the user's historical and current energy consumption. This section also describes the quantification of user engagement with the web application. The final section discusses the construction of the control group.

4.1. Time-of-use tariff

For this trial the TOU tariff is available during the summer daytime since the energy price at JEPX (Japan Electric Power Exchange) (JEPX [66]) tends to be high due to increased usage of air-conditioning. Fig. 1 shows the average price in half-hour increments on the JEPX spot market over the period July 2017 and September 2017. It is observed that the price of electricity starts to rise in the morning until the late evening. The period from 2pm to 10pm for weekdays is set for the peak time in this trial, encouraging consumers to reduce consumption due to relatively higher JEPX prices caused by high demand by industrial and residential customers and less solar generation.

During high demand periods energy retailers sell electricity at a loss if the wholesale cost exceeds the contracted retail price. If electricity consumption can be reduced during the peak period, this can create a win-win for consumers and retailers: a reduction in the negative spread of electricity sales for retailers which can be passed on to energy consumers in the form of a bill reduction.

The TOU tariff in this trial provides an incentive for the user to shift load from peak time to off-peak time (see Table 2). The reward takes the form of an energy bill reduction, as well as the avoidance of a bill increase if there is not a load shift. A peak rate (35 JPY/kWh - 35% higher than the flat rate) is applied during the 2pm–10pm weekday period, and an off-peak rate (20 JPY/kWh - 23% lower than the flat rate), is applied for all other periods including the weekend.

[2] This dataset is called CAMSL: CAMBRIDGE-SMAP-LOOOP given that this was a joint research programme between Looop Inc. (an energy retailer in Japan), SMAP ENERGY Limited (smart meter data analysis company in UK) (SMAP Energy Limited [65]), and researchers at the University of Cambridge.

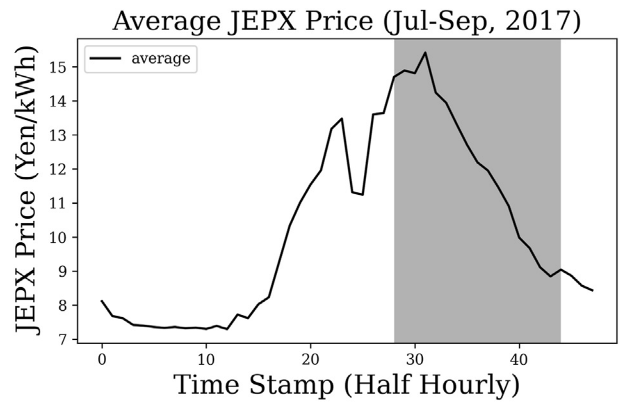

Fig. 1. Intra-day averaged price of JEPX spot market between July 2017 and September 2017. The horizontal axis is half-hourly time stamp from 0 (midnight) to 47 (23:30). The highlighted hours (2pm–10pm) are the peak hours in this trial.

Table 2
Tariff structure of flat and TOU tariff. Peak time is 2pm–10pm weekdays, and off-peak time is the rest including weekends.

Period	Flat tariff	TOU tariff	Difference
Peak Rate	26 JPY/kWh	35 JPY/kWh	35%
Off-Peak Rate	26 JPY/kWh	20 JPY/kWh	−23%
Availability	All times	1 July to 30 September 2018	

The flat tariff alternative is 26 JPY/kWh for all periods.

4.2. Web application

In this TOU trial a web application is provided to incentivise additional demand response beyond that provided by the TOU tariff. All TOU participants are required to sign up and register an email address in order to receive daily personal feedback through the web application. In this application the user can view their actual half-hourly consumption and personal baseline, generated from their average consumption for each time stamp during peak time in June 2018. This is then fixed for the entire trial period.

Fig. 2 is an example of the web application. The highlighted zone (14:00 to 22:00) represents the peak time. The fold line with small dots during the peak time is the personal baseline and the other line is the actual consumption of 24 July 2018. Peak reduction is observed in the day as the line of the actual consumption is mostly below the baseline during the peak time.

A *points* system is a core component for the *gamification* element in this trial. For the duration of the trial, users were able to view their electricity consumption via the web application. If for any day of the TOU period peak time consumption is less than the baseline, the user is rewarded 1 point per 0.01 kWh. No penalty is enforced if the consumption is higher than the baseline. The individual points and leader boards (rankings based on accumulated points) are updated daily, with rewards allocated on this basis.

To understand the relative effectiveness of the web application component, it is necessary to obtain a measure of individual-level engagement with the application. This is done by recording a

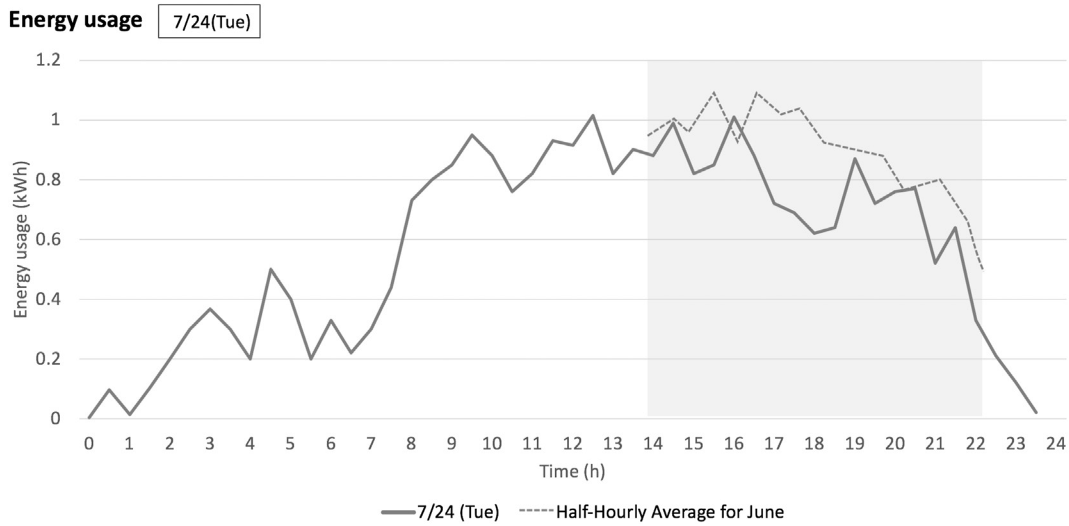

Fig. 2. Individual feedback and reward system.

number of measures of user activity on the web application using *Google Analytics* (Google Analytics [67]). These measures are defined as follows (Analytics Help [68]).

- Number of sessions: A session represents individual activities within the web application (checking the charts, viewing different pages, etc.) within a 30 min window. A single user can open multiple sessions in a day. A session ends after 30 min of inactivity or at midnight.
- Average session duration: The average time a user spends in a single session on the web application.

It is important to note that the web application became available at the beginning of the TOU trial. Given that the variables which record web activity do not represent ex ante information, these are used as a means to conduct ex post analysis to measure the correlation between online engagement and peak reduction.

4.3. Control group

To address the problem of self-selection whereby volunteers for the TOU trial are likely to have characteristics and preferences that are distinct from the general population, a control group was selected comprised of Tokyo-based consumers who are billed on their normal electricity tariff and given no web application. Since this TOU trial is part of commercial programme, a fully randomised control group is not available. The control group of 400 non-TOU users was randomly selected from Looop's customer base while maintaining the same distributions of demographic variables.

Fig. 3 presents the average load profile for TOU users and control group over the two periods. Note that during the pre-TOU period the average consumption of both groups are similar. However, during the TOU period, the consumption level of the TOU group is consistently lower than the control group. This phenomenon is more visible during the peak time (highlighted zone in Fig. 3).

4.4. Public dataset

The dataset used in this paper has been published and is publicly available on the web: https://github.com/smapenergy/CAMSL. The CAMSL dataset contains the items shown in Table 3. The dataset is available for free for both academic and industrial researchers to access upon the request.

The dataset includes 1423 households (1023 TOU users and 400 non-TOU users) in Tokyo between 1st July 2017 and 31st December 2018 (18 months). The dataset also includes raw data of 3337 customers who did not participate in the TOU trial. Each day has 48 half-hourly data points for energy consumption from a smart meter and each household has 579 days between 1 July 2017 to 31 December 2018, comprising a total of 27792 data points for electricity consumption obtained at each household for this dataset. The uniqueness of this dataset is the additional online engagement data recorded via web-application usage, the inclusion of which enables further studies related to gamification effects.

The CAMSL trial was designed from the ground up to be minimally invasive in terms of privacy. The intent to publish collected data was explicitly communicated to all participants at numerous stages in the sign up process, and participants had to give prior consent before signing up. This dataset does not store any identifying information about the specific house and area - beyond the general location of Tokyo - and releases only historical data.

5. Modelling framework

With the continued fall in computation costs, non-linear techniques such as Decision Trees (DT), Artificial Neural Networks (ANN), and Support Vector Machines (SVM) have been commonly used for medium-term electric load forecasting (Hernandez et al. [70] and Hahn et al. [71]). Here the primary objective is to train a model that minimises the loss between the predicted and actual values in a test dataset [72]. In constructing a load prediction model for individual customers under a TOU intervention, Kiguchi et al. [73] found that a Random Forest (RF) model (Breiman and Cutler [74]) outperforms neural network and linear regression for predicting the residential load after TOU intervention. RF represents an improvement of DT, given the construction a large number of DT since single trees are unstable, small changes in the training data can lead to very different trees structures (see Strobl and Zeileis [75]).

This paper builds on the previous work (Kiguchi et al. [73]), in developing a RF based regression approach that is capable of predicting the individual characteristics of winners and losers of a TOU tariff using smart meter data and other ex ante information. Although it is possible to approach the analysis as classification approach based on the identification of winners or losers, a

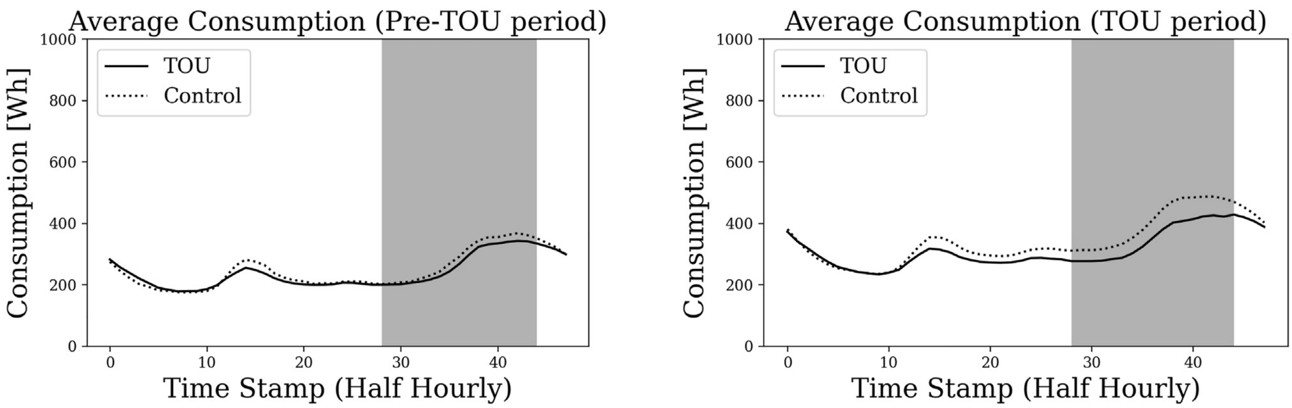

Fig. 3. Load curve of average consumption in TOU and control groups. (left: pre-TOU period, right: during-TOU period).

Table 3
Items in the CAMSL TOU dataset.

File name	File type	Description
README	text	instruction text
consumption_data	zip	from June 2017 to December 2018, 1023 TOU users and 400 non-TOU users
customer_info	csv	number of residents and house type
web_info	csv	sessions, average session duration (July 2018 to December 2018)
temperature_Tokyo	csv	hourly average temperature in Tokyo from June 2017 to December 2018 (Japan Meteorological Agency [69])
holiday_Japan	csv	from January 2017 to December 2018
non_tou.csv.gz	gz	raw data of consumption of total 3337 customers who did not participate in the TOU trial

regression approach is able to estimate the extent of individual peak reduction. This is of greater use considering that fact that energy companies want to see the transparency of the results, and design TOU tariffs rates accordingly. Therefore, regression approach is chosen for this paper.

5.1. Definition of winners and losers

The identification of the characteristics of individuals that are able to adjust consumption following the introduction of a TOU tariff involves a number of steps. First, the percentage change in peak electricity usage for household i over the period spanned by the TOU trial against the baseline is given by

$$\tilde{R}_i = 100 \times \frac{1}{n_p} \sum_{\tau \in Peak} \frac{\overline{C}^d_{\tau,i} - \overline{C}^p_{\tau,i}}{\overline{C}^p_{\tau,i}}, \tag{1}$$

where τ denotes the time index of 48 half-hourly data points and n_p is the number of time indices contained in the peak period (16 points over 8 h). $\overline{C}^p_{\tau,i}$ denotes the average consumption of the user i at time stamp τ over the pre-TOU period (30 days in June 2018); $\overline{C}^d_{\tau,i}$ is the counterpart for the TOU period (92 days from July to September 2018).

A key measure of customer engagement with a TOU tariff is the difference in peak consumption between the TOU and non-TOU users over the period spanning the introduction of the time-of-use tariff. This difference in peak consumption is referred to as *peak reduction* in the sense of comparing the change in peak consumption for both TOU and non-TOU users against the specific baseline. This method is useful to remove external factors such as seasonality.[3]

Peak reduction for individual household i in the TOU group is given by

$$R_i = \tilde{R}_i - \tilde{R}_c \tag{2}$$

where $\tilde{R}_c$ is given by

$$\tilde{R}_c = \frac{1}{n_c} \sum_{i \in C} \tilde{R}_i, \tag{3}$$

where n_c denotes the number of users in the control group. $\tilde{R}_c$ denotes the average percentage change against the baseline for households in the control group (C), who do not face the TOU tariff.

Although retail companies and policy makers care about the winners and losers as reflected in the distribution of R_i, as Kiguchi et al. [73] note, predicting demand response at the individual-level is difficult. To address this problem, a threshold rule to classify the users into two distinct groups of winners and losers is introduced, as opposed to using the full distribution of R_i. The classification is written as

$$S_{k,i} = \begin{cases} 1 & \text{if } R_i \geq k \\ 0 & \text{else} \end{cases} \tag{4}$$

$S_{k,i} = 1$ ($S_{k,i} = 0$) then indicates that household i has reduced (failed to reduce) peak load by more than k%, where k is an unknown constant.

5.2. Modelling method

The modelling method uses a RF based regression approach that estimates R_i, and then generate $S_{k,i}$ using (4). The individual level input variables are categorised into two groups: load-use variables and demographic variables. The first group includes the 1st to 4th moments derived from the historical half-hourly energy consumption recorded at each smart meter. The first moment represents the average consumption. The second moment (variance) represents the standard deviation and indicates the variability of usage. The third moment (kurtosis) is useful for determining the degree of symmetry of histograms and whether they are skewed. The fourth moment (skewness) measures the heaviness of the tail, and hence a measure of the number of outliers.

[3] This represents the same methodology as used in the 2011 Irish TOU trial (Commission for Energy Regulation [52]).

Table 4
The four statistical moments of the daily consumption data in pre-TOU period.

Group	No.	Average	Variance	Skewness	Kurtosis
TOU	1023	120.1	685.1	1.49×10^4	1.05×10^6

Kiguchi et al. [73] found these moments to be an important predictor of electricity consumption. For example, the average consumption of the given user (i) for the pre-TOU period is written as $\frac{1}{48}\sum_{\tau=1}^{48}\overline{C}_{\tau,i}^{p}$. By summing over 48 timestamps, the average value for a given day during the pre-TOU period is calculated. These values are summarised in Table 4.

The second group of input variables includes a limited number of demographic variables: number of residents (from 1 to 5 or above) and household types (detached, flat). Detached house is defined as a free-standing residential building, and flat (apartment) is defined as self-contained housing unit that occupies a part of a larger building.

5.3. Evaluation

The introduction of $S_{k,i}$ turns this regression problem into a binary classification problem. A commonly used performance measure for binary classification[4] is defined as the total number of the correctly classified observations divided by the total sample size, namely

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}. \tag{5}$$

TP (true positive) indicates the number of households where $S_{k,i} = 1$ and $\hat{S}_{k,i} = 1$. FN (false negative) indicates the number of households where $S_{k,i} = 1$ and $\hat{S}_{k,i} = 0$. FP and TN can be similarly defined.

Beckel et al. [77] advocate the use of the Matthews Correlation Coefficient (MCC) when classes are imbalanced. MCC utilises a penalty function to reward true positives (the underrepresented class). MCC is given by

$$\text{mcc} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{6}$$

MCC ranges between 1 (-1) when there is total agreement (disagreement) between the observed and estimated classes. A value of 0 indicates random classification. This paper uses MCC to quantify the performance of the classifiers.

6. Results

In this section, the classification performance of the model is examined. Section 6.1 evaluates the overall model performance, and discusses the potential benefit of this model In Section 6.2 individual feature importance is examined, and essential variables for the model construction are identified. In Section 6.3, the importance of online engagement in detail is considered. Revealing the relationship between online engagement and the TOU trial outcome is one of the unique points in this paper, and gamification is a key tool to enhance the level of online engagement with marginal financial cost.

6.1. Model results

In Fig. 4 the distribution of $\hat{R}_i$ and R_i, which are the predicted and actual peak reduction for individual household respectively, is presented. It is observed that for the majority of customers $\hat{R}_i > 0$, indicating a reduction of load over the period of the TOU tariff. Out of the 1023 households, the model predicts 854 instances of load reduction ($\hat{R}_i > 0$) versus 742 observed. The mean of $\hat{R}_i$ and R_i are 15.9 and 16.5 kWh per day. The variance of $\hat{R}_i$ and R_i are 488.3 and 2647.2.

The accuracy of the RF-based regression model at the individual level was calculated using mean absolute percentage error, which was 60.4%. The fact that the distributions of $\hat{R}_i$ and R_i are different is to be expected given the difficulty of predicting individual consumption. The relatively low accuracy of the regression model result provides motivation for applying the binary classification rule (winners and losers) instead of predicting individual consumption, which helps to practically interpret this model's results given this limitation of the dataset in this paper.

The size of this dataset might cause this accuracy, and therefore future works using larger dataset for training the model could improve the regression accuracy. A practical approach to establish a larger dataset that is known to be successful in a domain such as image recognition (Chollet [78]) is the fine-tuning methods, where the model is trained on an existing dataset and then tuned on a newly collected dataset. Considering this possibility, the publicised dataset CAMSL is beneficial for further TOU analysis studies.

The predicted distribution of $\hat{R}_i$ is then utilised for classifying winners and losers. That is, the classification model identifies the winners ($\hat{S}_{k,i} = 1$) and losers ($\hat{S}_{k,i} = 0$) for a given threshold k. Table 5 show the MCC results with different threshold value k (from -30 to 30). Given MCC values are greater when $k > 0$, indicates that the proposed model performs better at predicting instances of peak load reduction. This indicates that potential winners are comparatively easier to detect by the model.

One potential application of the proposed model is for energy suppliers to target potential households based on their budget. The budget constraint determines how many households can be targeted for the marketing of the DSM programme. Energy suppliers can target prospective winners of the DSM programme, which are given by the proposed model that estimates R_i. The distribution of $\hat{R}_i$ shown in Fig. 4 provides information to decide the optimal k by calculating the number of $\hat{S}_{k,i} = 1$, i.e., prospective winners.

Table 6 presents a confusion matrix which provides a measure of model performance in terms of the number of correctly identified predictions. The table is presented for the case where MCC is highest ($k = 20$). In this instance, predictive performance based upon a classification of individuals around the threshold ($\hat{R}_i > 20\%$) is evaluated. From the table, it is observed that 50.2% (536 out of 1023) of customers are observed to reduce peak load by more than 20% ($R_i > 20\%$) in the TOU tariff trial. It can be understood that an energy supplier offering this TOU tariff to this pool of individuals would have an equal number of winners and losers.

This approach might be used by energy suppliers to deliver a TOU tariff. For example, based on Table 6, a company might restrict a TOU tariff to those individuals whose characteristics match those that are predicted to reduce peak load. If this subset of predicted winners (722 users) were to join the programme, 63.0% (455 users) will become winners in this trial. This model can therefore increase the

[4] See Sokolova and Lapalme [76] for an extensive overview of different performance measures for classification tasks.

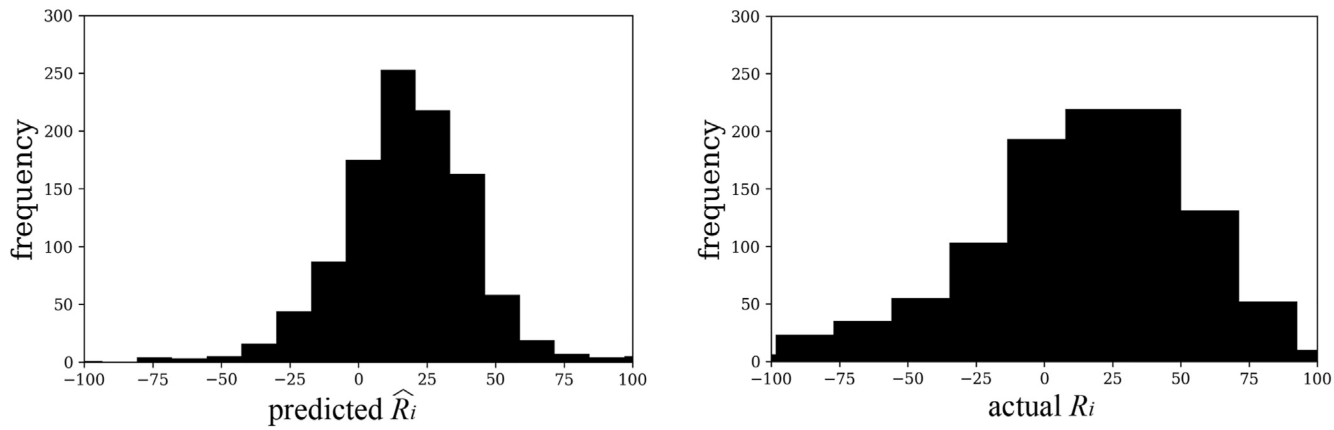

Fig. 4. Distribution of the model result (left: $\hat{R}_i$, right: R_i).

Table 5
MCC result with different threshold value k.

k%	−30	−20	−10	10	20	30
MCC values	0.17	0.14	0.16	0.36	0.38	0.29

Table 6
Confusion matrix for $k = 20$.

	$S_{k,i} = 1$	$S_{k,i} = 0$	
$\hat{S}_{k,i} = 1$	455	267	722
$\hat{S}_{k,i} = 0$	81	265	346
	536	532	1023

effectiveness of the TOU programme by 25.5%,[5] and identify the majority of potential winners (84.9%) before a tariff is implemented.

6.2. Feature importance

Table 7 reports values of the Gini coefficient values for each feature. This measures the change in the prediction error when data for a single feature is permuted while the others are left unchanged. This makes it feasible to decide which features should be used given the cost of collection and importance for the model performance of $\hat{R}_i$ prediction (Breiman [79]). The results demonstrate that features derived from historical load data are the dominant factors for the predictive performance. Note that variance comes first among all variables, followed by the mean, kurtosis and skewness.

In contrast the contribution of the household characteristics are limited. As has been found in a number of other studies (see, for example, O'Neill and Weeks [29]), demographic characteristics are reflected in the historical load profiles, suggesting that these static features are not so important.

6.3. Importance of engagement

Given that the web application was launched at the start of the TOU tariff trial, engagement variables represent ex post information and as a result are not used as a part of the modelling. However, it is possible to determine if these variables correlate with the model

Table 7
Feature importance.

Variable	Gini coefficient
average	23.82%
variance	24.17%
skewness	16.72%
kurtosis	20.72%
number of residents	7.59%
household type	6.98%

results. The average number of sessions of the responsive households ($S_{ik} = 1$) and the others ($S_{ik} = 0$) during the TOU period were 6.68 and 3.71 respectively, and the difference was statistically significant ($p < 0.05$). This result suggests that the degree of online engagement correlates with the outcome of the TOU price signalling.

The results suggest that if an energy company can encourage customers to be more active on the online service (for example, by providing gamification features such as points and rewards), this may generate a greater degree of demand response. This can provide an additional opportunity for energy companies to optimise TOU planning since they often believe financial incentives (similar to tariff incentive in Section 4.1) are the only the way to motivate the customers.

Sophisticated gamification design is equally important for a TOU trial, and implementing gamification could be much cheaper than monetary rewards at a large scale deployment. As noted, in this trial measures of user engagement variables are obtained ex post. If a similar programme is planned in the future and some participants rejoin the programme, these variables could become ex ante information, and used as a proxy for user engagement.

7. Conclusion

Time-of-use (TOU) tariffs and other kinds of time-dependant pricing can be mutually beneficial, resulting in a cost reduction for both energy companies and customers if the customer responds to the price signalling. This paper provides a data-driven approach to identify the characteristics of households that would either be positively or negatively affected under a TOU tariff, using only ex ante information such as smart meter data. Such a model can maximise the outcome of a TOU programme and reduce the chances of adverse outcomes for participants.

The key findings of this paper can be summarised as follows. First, the predictive model performs better for the identifying winner rather than identifying losers. The highest model accuracy

[5] the increase of 25.5% represents a move to 63.0% from 50.2%.

is achieved 0.38 (MCC score) for the classification, where *k* is set to be 20. Gini coefficient values reveal that historical smart meter data is the main contributor to this model performance rather than household characteristics. This result indicates that such a model can help energy companies to deliver a TOU tariff to potential winners efficiently.

Second, the level of online engagement is confirmed to have a significant influence on a TOU tariff outcome. Online engagement variables meaningfully contribute to the model performance, and the engaged customers are significantly more responsive to the price signalling compared to the others. These results indicate that enhancement of the online engagement needs to be considered for a TOU tariff design, and good gamification can bring a favourable outcome for energy companies at relatively low cost.

This paper also publishes a new public dataset (CAMSL) of 1423 households in Tokyo, Japan, including 18 months of historical smart meter data, household characteristics and online activity variables. The authors believe that a scarcity of public datasets has prevented researchers from developing models and testing external validity. This paper demonstrates hopefully the first of many models using this CAMSL dataset. The dataset is available for free for both academic and industrial researchers to access upon request.

This work and the authors' previous work (Kiguchi et al. [73]) have demonstrated data-driven modelling techniques of consumer demand response following a TOU tariff introduction at residential scale, unleashing the power of smart meter data. Academic research institutions are also able to use the published dataset to further optimise the proposed TOU model, potentially incorporating data on other flexible resources such as heat pumps and electric vehicles. These works could help consumers and energy suppliers in making the best use of the increasing penetration rate of intermittent clean energy resources and make the energy more affordable and secure.

Credit author statement

Yohei Kiguchi: Conceptualization, Methodology, Writing- Original draft preparation, Investigation, Project administration, Data curation, Software, Validation, Visualization, Formal analysis. Melvyn Weeks: Supervision, Writing- Reviewing and Editing. Riku Arakawa: Data curation, Formal analysis.

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.

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