# Residential Demand Response using Electricity Smart Meter Data


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This dissertation is submitted for the degree of
*Doctor of Philosophy*

Peterhouse December 2021

# Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 65,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

Yohei Kiguchi
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# Abstract

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The electricity industry is currently undergoing changes in a transitioning period characterised by Energy 3D: Digitalisation, Decentralisation, and Decarbonisation. Smart meters are the vital infrastructure necessary to digitalise the energy system as well as enable advancements in decentralisation and decarbonisation. As of today, more than 500 million smart meters have been installed worldwide, with that number expected to rise to several billion installations over the decade. Smart meters enable electricity load to be measured with half-hourly granularity, providing an opportunity for demand-side management innovations that are likely to be advantageous for both utility companies and customers. Among these innovations, time-of-use (TOU) tariffs are widely considered to be the most promising solution for optimising energy consumption in the residential sector, however actual use is still limited.

The objective of this thesis is to investigate opportunities and problems related to TOU tariffs utilising smart meter data at the national level. The authors have identified four major research gaps which need to be filled in order to expand commercial applications of TOU tariffs. These gaps are the described and addressed in the following chapters: the "TOU load adaptation forecasting problem", the "TOU winner detection problem", the "TOU public dataset problem", and the "excess generation forecasting problem".

This thesis demonstrates three modelling approaches and one new TOU dataset (CAMSL). A significant contribution to the field is through the discover of new summary statistical features (statistical moments) and assesses the capacity of these to encapsulate other more widely used explanatory variables of demand response. The thesis is concluded by discussing future works and policy implications, such as the necessity of the more tailored modelling works and public live-stream of smart meter data, which could accelerate the roll-out of the demand side management at the residential sector.

# Acknowledgements

In September 2013 when I arrived in Cambridge for a master's degree, I could not even imagine the day I am writing these words. The journey from the first day in Cambridge to now has been long and winding, tough and stressful, but full of hopes, dreams, and appreciation to all people who have provided me unconditional support. Thus let me begin this chapter to summarise my journey behind this thesis.

The Fukushima Nuclear Disaster in 2011 initially sparked my interest in the energy sector, and has merged with my academic passion for data science to form my research theme of energy data analysis. I was hoping that my study at Cambridge will equip me with new skills and perspectives to empower my future career, and I that in turn I can make my own contributions to the energy transition. Despite such an ambitious hope, my background was different from other engineering students, and I was initially struggling to decide my path. I clearly remember the day in October 2013 when I firstly met Dr. Ruchi Choudhary via introduction from Professor Kenichi Soga and Professor Michael Pollitt. She understood my motivation, and allowed me to transfer to her course without the typical completion of a masters course to start a PhD research for smart meter projects in January 2014. At the same time, Mr. Yoshiyuki Iwasaki, the founder and CEO of EPCO, a listed company on the Tokyo Stock Exchange, promised to provide sponsorship for my work with Ruchi. His generosity comes from the shared passion for the new energy transition, and we were connected via an introduction from Mr. Takumi Shibata and Mr. Akira Kamitomai. My first year of the PhD could not be more thrilling. It included taking courses of Machine Learning by Professor Zoubin Ghahramani and Professor Carl Edward Rasmussen, Applied Bayesian Statistics by Professor David Spiegelhalter, and participating in the Machine Learning Group every Thursday.

My direction has since shifted as I was involved with a foundation of a privately funded research body named Cambridge Energy Data Lab Limited, which subsequently founded ENECHANGE (online energy switching platform based in Japan) in 2015, and SMAP ENERGY (smart meter data analytics platform based in United Kingdom) in 2016. Especially, SMAP ENERGY was founded based on my PhD research works, and Cambridge Enterprise Limited became the shareholder of the company at the foundation - cementing our status as a

University spin-out startup. Involvement with these startups has been fascinating, though it created time conflicts with the parallel work towards the completion of the PhD; therefore I submitted for a temporary withdrawal from the University in October 2017 to focus on these startups. Since then, I became CEO of both companies and merged SMAP ENERGY into ENECHANGE to form ENECHANGE group. ENECHANGE group became a listed company on 23rd December 2020 at Tokyo Stock Exchange Mothers, as the first energy-tech listed company in Japan, and recognised the one of the fastest growing companies in the clean-tech field. ENECHANGE has expanded its business lines from energy switching to smart meter data analysis, demand response, renewable energy management and electric vehicle charging - all strategies built from the knowledge gained in my Cambridge studies. Alongside these intensive roles, I have managed to work on academic papers by publishing two journal papers in *Energy*, and writing up the PhD thesis. I formally reinstated in June 2021 to complete the PhD.

I could not express my appreciation more to the University of Cambridge and the people who I have met throughout my journey, and my space here is limited. I first start by thanking again my supervisor Dr. Ruchi Choudhary. From the beginning of my research to the time I write these words, Ruchi has been incredibly patient, supportive and dedicated (despite my temporary withdrawal for some years in between), always allowing me the space and time to explore new ideas, both in the fields of engineering and beyond. Without her, I do not believe I could have achieved either business or academic outcome. More than that, I will remember fondly times with her and her husband Serge in Tokyo.

I have to thank my second advisor, Dr. Melvyn Weeks for his simultaneous encouragement and guidance. It has been a great opportunity for me to learn from him over the last years, especially in the fields of econometric and behavioural analysis where his knowledge and expertise is unequivocal. Discussions with him at a cafe in Cambridge have been intellectually exciting and inspiring, allowing me to form the foundation of this thesis idea.

I have to also thank Mr. Yoshiyuki Iwasaki for sponsoring this research. His generous and patient support has given me an opportunity to pursue the idea of this PhD journey, and he has also unconditionally supported and invested the businesses from the day one. He has been acting as a sponsor, mentor, investor, and more personally as a reliable father throughout this whole journey. I could not respect him more than anyone else in my life.

Many thanks go to my colleagues in the Energy Efficient Cities Initiative, who have been a pleasure to work with over the years. In particular, special thanks to Dr. Adnan Mortada, Dr. Yeonsook Heo, and Rebecca Ward, who have helped tremendously in discussing the ideas and methods behind this thesis and motivated me throughout.

I would also like to give thanks to my colleagues at the company who have travelled though this journey from the days studying in Cambridge to an array of entrepreneurial challenges, and finally to an exciting new role as a publicly listed energy-tech company. In particular, I'd like to recognise Paul Monroe, Riku Arakawa and Ippei Arita, who have shared memories of the early days in Cambridge as a founding member, and continued the journey with me over the many years. You have been a consistent source of intellectual stimulation and my indispensable colleagues who genuinely share a passion for the energy transition.

Lastly, to my parents, Toyoko and Takashi and my sisters Kaori and Yumi. I hope you understand that my family was often on my mind over the last years, though maybe I did not show it as frequently as I could have. Family visits to Cambridge were unforgettable memories for me, and I am pleased to see that two younger sisters were inspired to come to study in the UK following my path (both went to Oxford). My only regret is that I could not deliver this thesis earlier for my grandmother Shigeko who was the biggest supporter in my life and wishing to attend my graduation ceremony, but passed away on 15th January 2016.

I finish my gratitude with my female French Bulldog Lon, who has always patiently sat next to me as I worked on this thesis. I know it has been boring for you Lon, but your desire for a walk encourages me to focus and work efficiently.

Thank you so much everyone for having always been supportive of me for such a long journey (2013 to 2021).

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# Nomenclature

**Acronyms / Abbreviations**

AC Alternating Current

ANN Artificial Neural Network

ARD Automatic Relevance Determination

CAMSL Cambridge- SMAP ENERGY- Looop

CART Classification and Regression Trees

CEDL Cambridge Energy Data Lab, ltd.

CPP Critical Peak Pricing

D-FIT Domestic Feed-in Tariff

DC Direct Current

DHW Domestic Hot Water

DNN Deep Neural Network

DR Demand Response

DSM Demand Side Management

DSO Distribution System Operator

DT Decision Trees

EECi Energy Efficient Cities Initiative

ELM Extreme learning machine

EV Electric Vehicle

FC Feature Cluster

FFNN Feed forward artificial neural networks

FIT Feed-in Tariff

GP Gaussian Process

GPML Gaussian Processes for Machine Learning

HES Head-End System

HME hierarchical mixture of experts

HMM Hidden Markov model

HVAC Heating, Ventilation, and Air Conditioning

HVAC Heating, ventilation, and air conditioning

IEA International Energy Agency

JEPX Japan Electric Power Exchange

JPY Japanese Yen

KM K-means

kNN k-nearest neighbour

LFM Load forecasting model

LMGI Load matching and grid interaction

LR Linear Regression

MAE Mean absolute error

MAPE Mean Absolute Percentage Error

MCC Matthews Correlation Coefficient

MLR Multivariate linear regression

MSE Mean squared error

Net ZEB Net-Zero Energy Building

NN Neural Network

nRMSE Normalised Root Mean Squared Error

PG&E Pacific Gas and Electric

PRML Pattern Recognition and Machine Learning

PV Photovoltaic

RETS RETScreen Photovoltaic Project Model

RF Random Forest

RMSE Root Mean Squared Error

RPS Renewable Portfolio Standard

RW Random walk

SCE Southern California Edison

SUSDEM Stochastic Urban Scale Domestic Energy Model

SVM Support Vector Machine

TOU Time of Use

UK United Kingdom

# Chapter 1

# Introduction

## 1.1 Energy 3D

Since the 1970s, fossil fuels have contributed 60–70 % of the global energy production (Ventures [277]), but this balance is changing. Political and social factors have helped to drive the acceptance of renewable energy sources, and recent technological advancements in renewable energy, reduced prices of battery storage systems, and enhanced decentralised power production are speeding up the global transformation of the energy sector. Climate change has been an international issue for a long time and was propelled globally by green activists and political parties, though industries have moved more cautiously.

The Paris Agreement of 2015 and the Fifth Assessment report of Intergovernmental Panel on Climate Change clearly outlined the severity of the issue, establishing the target that the global average temperature rise needs to be kept under 2°C over pre-industrial levels. (Rogelj et al. [233], Wang and Su [279]). The 3D's of the new energy system - or Energy 3D - are pressuring industry to move towards a low-carbon economy. According to industry experts, Energy 3D refers to the decarbonisation, decentralisation, and digitalisation of the energy sector, which collectively would result in a dramatic overhaul of the existing energy and transport infrastructure. Figure 1.1 summarises these 3 Ds of Energy 3D.

Decarbonisation refers to the continuous adoption of sustainable energy sources, such as wind and solar, and the move away from the usage of fossil fuels. Targets for decarbonisation at a global level were established for the first time in 2015 at COP21 in Paris. In 2016, the COP22 in Marrakech, named "the COP of the action", offered the opportunity to execute the Paris COP21 agreement (Ghezloun et al. [105]). The Paris agreement identified that climate change was associated with emissions of human-made greenhouse gasses (GHG) and proposed measures to maintain global average temperature increases to under 2°C and, if possible, 1.5°C. According to the BloombergNEF [28] report, renewables will produce about

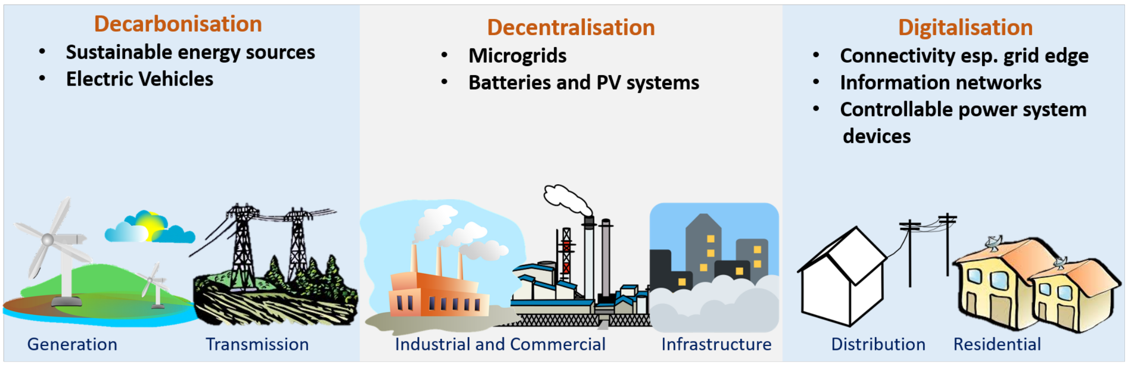



Fig. 1.1 3 Ds of Energy 3D (based on Forum [97])

62% of total energy by 2050, of which solar and wind will produce about 48% and the power production from fossil fuels will decline to only 31%. This reduction is driven mainly by the need for 12 TW of new investment in energy generation by 2050, which expects 77% to be for renewable energy resources and is forecasted to cost $13.3 trillion. Figure 1.2 illustrates the global trend of energy production from all sources of energy.

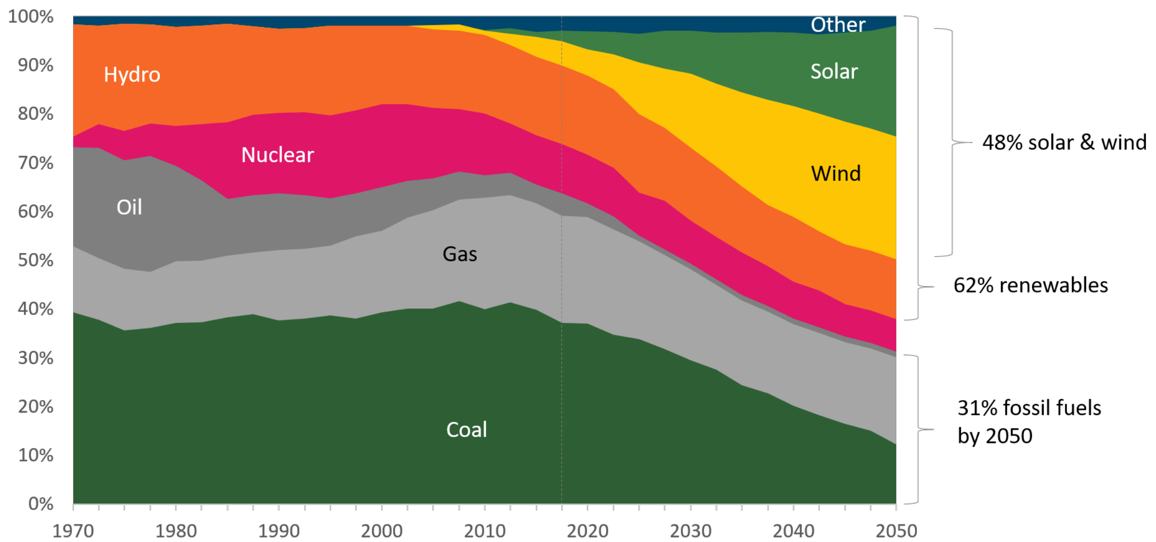



Fig. 1.2 Global trend of energy production (based on BloombergNEF [28])

Electric vehicles (EVs) can further promote the decarbonisation of energy and transport. In addition to decreased tailpipe emissions, the charging of EV batteries from electricity - ideally generated from renewable sources - can result in net carbon reduction and supplement broader grid decarbonisation initiatives. For instance, EV smart charging systems can make it possible to store about one fifth of solar power generated in Great Britain and can release this energy when required (Corliss [50]).

Decentralisation, the second D of Energy 3Ds, is a framework of reallocating tasks, power, things, and people away from a single organisational structure into a broader distribution of control. In decades past, energy generation was generally relegated to large power plants owned by public utilities. However, technological advancements have reduced the cost of generating and storing energy across smaller systems at a price point where individual ownership is feasible.

Today, homeowners and businesses are investing in their own energy systems such as batteries and photovoltaic (PV) systems to supply their own energy needs. There are a growing number of cases where energy "microgrids" capable of supplying the entirety of their energy demand at the city, neighbourhood, or even building level. This decentralisation has benefits in that it increases the resilience of the grid - as the connected individuals have flexibility to disconnect or even become suppliers to the grid itself - but is countered with an increased challenge of management as the individual assets are no longer singularly owned and controlled.

Digitalisation, the last D for Energy 3D, where previously manual and mechanical processes and devices are connected to information networks, are generating data, and - increasingly - are remotely controllable. "Smart" technologies are rapidly being used in the energy system, but much of this ecosystem is still full of outdated resources that are no longer fit for the technological world. The rise in the volume of distributed devices in the power system such as electric vehicles, solar panels, and batteries has led to the generation of large volumes of data. In addition, existing measurement devices are being upgraded and are increasingly able to collect more data - both in form and frequency. The primary example of this for the energy system is with smart meters, which enable the collection of energy consumption data in the order of minutes or hours. The coming sub-sections of this chapter explain in detail how smart meters come into the equation of Energy 3D.

## 1.2 Electricity Smart Meter

A general smart meter is a tool capable of measuring the physical parameters of the energy flowing via its borders, tracking events (e.g. shutdowns, alterations in predetermined rated power), and digitising and transmitting this data to a central procurement system. In most systems, an electrical smart meter gathers data from a site and then sends the reports to the Distribution System Operator (DSO). This report encompasses not only the energy flows, but also voltage level, power factor, disconnections, errors, and more. The DSO then uses information both for network management (e.g. managing losses in power network) and for supplying authenticated data to retailers, which can be used primarily for billing purposes as well as for customer services.

In consideration of the smart meter's critical role in the electricity supply chain, multiple policymakers have specified its key features. As per EU Commission Directive 2004/22/EC on Measuring Instruments (MID), a smart meter shall display metering results directly at the customer location through a monitor or another display device (Directive et al. [66]). It must be easy to use, long-lasting and must be reasonably future-proofed. Data for several days or over one type of physical data (e.g. energy consumption, reactive energy, active energy, and voltage) can be encrypted and recorded in the smart meter log to cope with the potential inaccessibility of the communication network used in the Head-End System (HES) data exchange with the DSO.

### 1.2.1 First Generation Smart Meters

In the first generation (1G) of electrical smart meters, measured information shared between the smart meter and the Head-End System (HES) generally goes through two steps as shown in Figure 1.3. In the more popular smart meter infrastructure, the first step makes a connection between the smart meter and the so-called data concentrators, which are generally located in a secondary substation with low voltage (LV)/ medium voltage (MV) transformers. The second connection enables measurements, obtained from data concentrators, to be sent to the HES. This data concentrator is a smart platform that obtains, processes, and reassembles thousands of data measurements from smart meter prior to transmitting this information to HES. If the communication with a smart meter is obstructed, it can also request new data attainment.

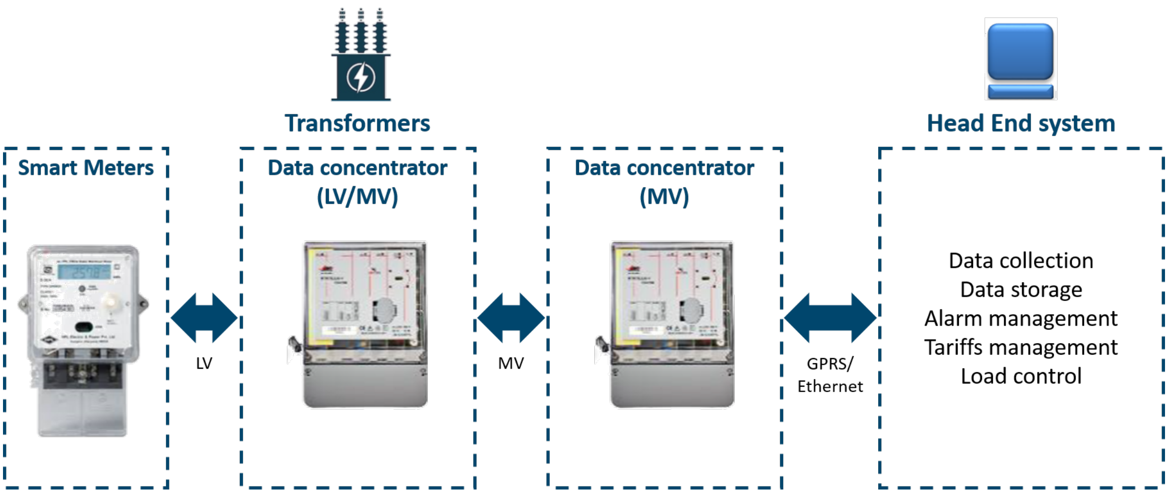



Fig. 1.3 Advanced Metering Reading Basic Architecture (based on International [139]).

Smart meters, data concentrators, and HES are the primary components of this Advanced Metering Infrastructure (AMI) (CEN and CENELEC [39]). AMI plays a crucial part in electricity delivery systems by storing load profiles and allowing two-way data flow (Mohassel et al. [189]). Theoretically, communications inside the AMI allow data attainment from smart meters to HES. However, the data can be exchanged in both ways - that is, from HES to smart meter and from smart meter to HES - in almost every case. Nonetheless, this needs a more complicated architecture with several communication technologies such as Wide Area Network, Local Network, and Neighbourhood network, as depicted in Figure 1.4. This permits DSOs to perform several operations remotely, such as taking meter readings or remotely disconnecting a customer with unpaid bill. The previous structure as shown in Figure 1.3 is referred as Advanced Metering Reading (AMR), and this advanced architecture with communication technologies is known as Advance Metering Management (AMM).

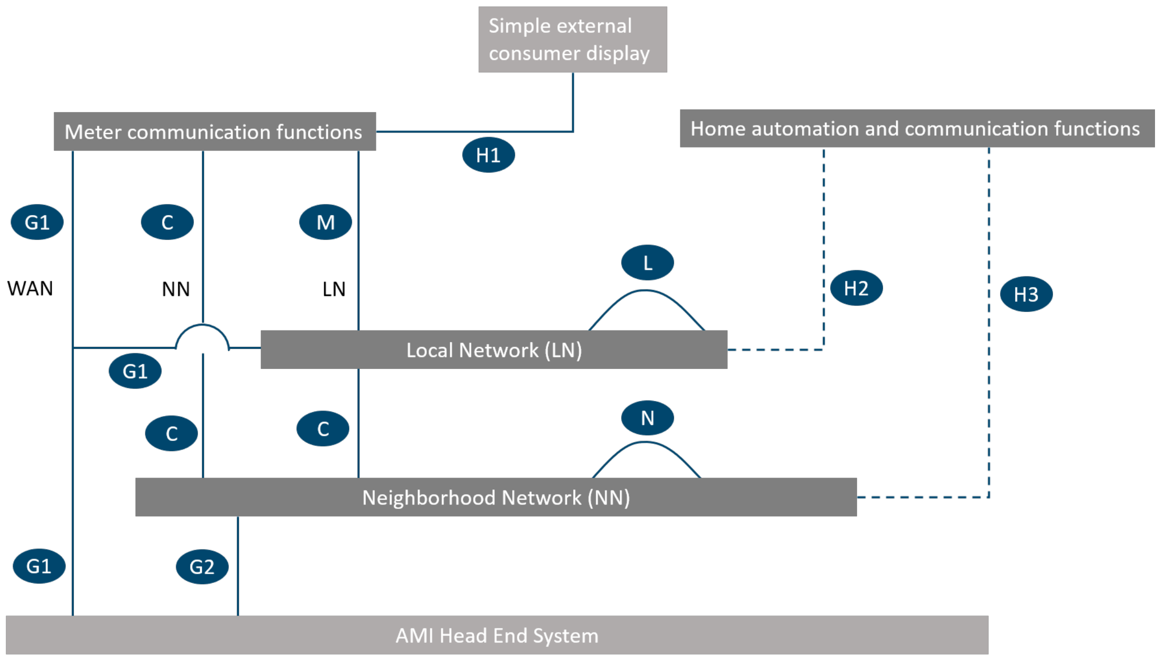



Fig. 1.4 Advance Metering Management Functional Structure (based on CEN and CENELEC [39]).

Currently, researchers are using various technologies to communicate measured parameters to the data concentrator. The most preferable way is communication through Power Line Communications (PLC) or Transmission Line Communication (TLC) as its deployment is possible in the current electrical system and it doesn't need a separate infrastructure. The electrical utilities can control it directly and it is reachable even in installations deep within a building. This also mitigates the requirement for the DSO to attain the telecommunication services, even though they are already being used for linkage of HES to the data concentrator.

Moreover, wireless communication technologies, such as Wireless Meter-Bus (WM-Bus), operating at sub-GHz frequencies are common substitutes for gaining data from smart meter. However, their main limitations are that frequency planning is required to make sure less interference and a separate communication network must be deployed.

### 1.2.2 Second Generation Smart Meters

Italy is leading the smart metering deployment in Europe since it was the first EU nation to announce advanced, remotely-read smart energy meters for deployment to LV customers on a broad scale. Today, over 35 million of 1G smart meters are in service (Italian Authority of Electricity and Water [143]). The Legislative Decree 102/20143 in Italy transposed the EU Energy Efficiency Directive (EED 2012/27/EU) and regulatory authority ARERA in Italy was given the charge of setting the minimal functional capabilities of the second-generation smart meters (Italian Authority of Electricity and Water [143]). In 2016, the regulatory authority issued the following two decisions (Engie [81]):

- Decision 87/2016/R/eel specified the technical requirements and anticipated efficiency standards of second generation (2G) smart meters with consideration for improving precision and accuracy of metered data for all LV users.
- Decision 646/2016/R/eel introduced a tariff regulation that established standards for recognising the capital expenditure of smart metering systems in line with their functionality and performance levels as characterised by Decision 87/2016/R/eel.

The new 2G smart meters were designed to improve customer service, additionally reducing the billing practise of estimated energy usage rather than true energy usage, and enhance precision and accuracy of the measuring data for all LV connected consumers. The latest communication attributes directly bring the raw metered data to the end-users and also direct these readings to the corresponding DSO. The DSO needs this data for providing services such as home automation, demand response programmes, and customer awareness initiatives. Pitì et al. [221] compared the 1G and 2G smart meters on the basis of metered data and sampling data resolution as shown in Table 1.1.

According to Navigant [195] research report of 2019, many markets across the globe are continuing the deployment of 1G smart meters, whereas the dynamic and competitive economies in North America and Europe are pushing forward with initiatives of the 2G smart meters. Differences arise in implementation and project readiness, with certain nations such as UK and Italy finishing their 1G smart meter deployments, while others, such as most of the Middle East and India, are only starting to execute their smart meter projects. Figure

Table 1.1 Comparison of 2G and 1G smart meters (Pitì et al. [221])

| Metering Data | 2-G Smart Meter | 1-G Smart meter |
|---|---|---|
| Active energy withdrawn | 15 min | 3 values per month |
| Active energy Injected | 15 min | 3 values per month |
| Reactive energy withdrawn | 15 min | 3 values per month |
| Reactive energy Injected | 15 min | 3 values per month |
| Active power withdrawn | 15 min (peak) and instantaneous value (1s) | 30 min (peak) |
| Active energy Injected | 15 min (avg) | No |
| Min/max voltage | 1 per week | Only occasionally |
| Voltage in limits | Yes, compliant with EN50160 | Only occasionally and not compliant with EN50160 |
| Outages | On event occurrence | Implemented but not used |

1.5 depicts the number of 2G smart meter or SMETS2 that are installed in UK in 2019 and Figure 1.6 illustrates the 2G SMs deployment timeline of Italy (as decided by ARERA).

In UK, according to the Data Communications Company [57] the increase in number of 2G smart meters - or SMETS2 - installations in 2019 (3.3 million) can be seen to be more than 6 times the number of installations in 2018 (0.5 million). Furthermore, on 27 February 2020, British Gas reached 4 million installations of SMETS2 (Data Communications Company [57]). Notably, their director of Industry Development also claimed that they can see the benefit of smart meters on their consumers' monitoring and adaptation of their electricity usage to minimise pollution.

In Italy, ARERA accepted the 2G smart meter deployment proposal for E-distribuzione company in Rome with Resolution 222/2017/ R/eel from 2017. The deployment proposal covers a 15 year span from 2017 to 2031 and involves a national replacement of its 31.8 million 1G smart meters with 2G smart meters to achieve a penetration of 80 % by 2022. E-distribuzione was able to follow the 2G smart meter deployment plan as it already deployed about 1.4 million 2G SMs by November 2017 (also see Figure 1.6).

2G smart meters can also send non-authenticated raw data, in real-time, directly to the concerned user. By using in-home devices (IHD) or Home Area Network (HAN), 2G-smart meter can directly communicate and measurements may appear on a local monitor or smartphone device, providing analysis on consumption data and guidance for decreasing electricity bills. Additionally, a smart meter that can enable two-way communication can also get notifications from an IHD requesting to perform certain operations or get specific

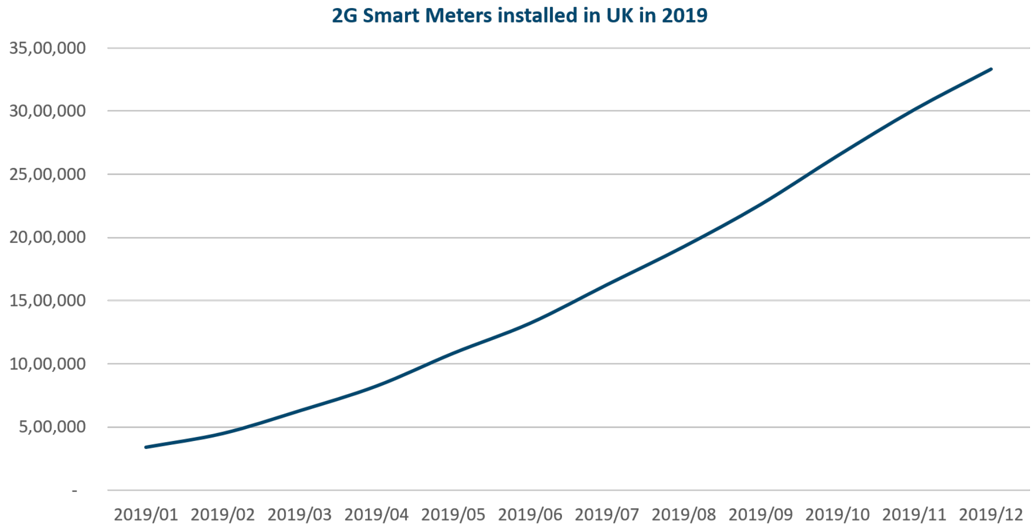



Fig. 1.5 Number of 2G Smart Meters installed in UK in 2019 (based on Data Communications Company [57]).

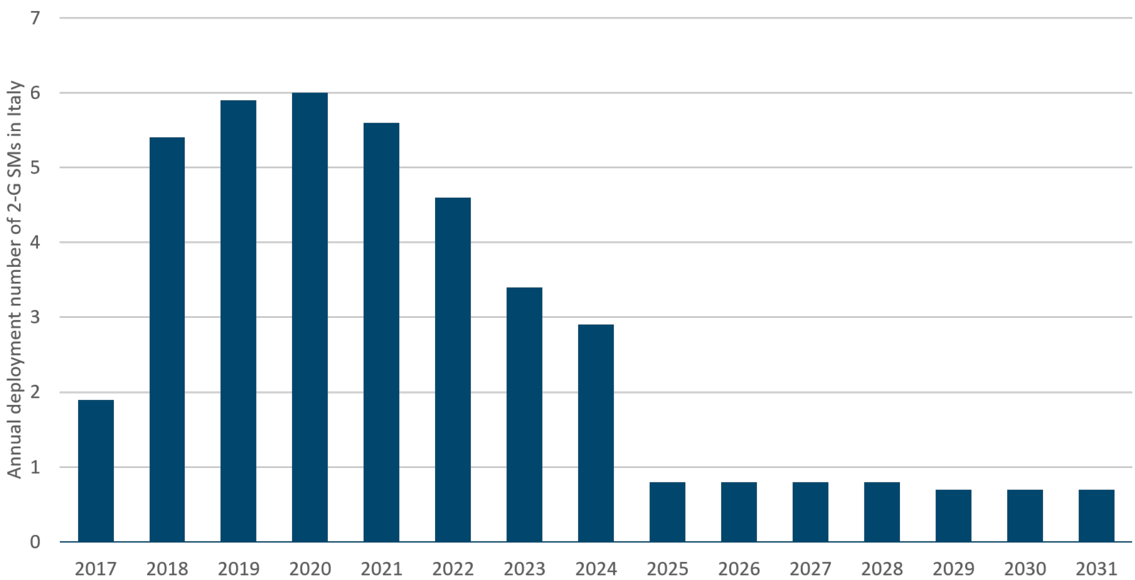



Fig. 1.6 Planned annual deployment number of 2-G SMs in Italy (based on Engie [81]).

information. These systems are naturally more susceptible to cyber- and electrical-security problems, which must not be disregarded.

Furthermore, at the HES end, validation process analyses raw data to see if the data are valid and complete, or, if that is not the case, it applies advanced algorithms to reconstruct missing measurements. Upon validation, the authenticated readings are ready to be sent to the retailers for billing purposes. However, in the case with millions of users and daily measurements with fine granularity, even with 100 percent data accuracy this validation process can consume many hours before the measurements can be sent to the retailers. Figure 1.7 illustrates the evolution of smart meters from 1G to 2G (Pitì et al. [220]).

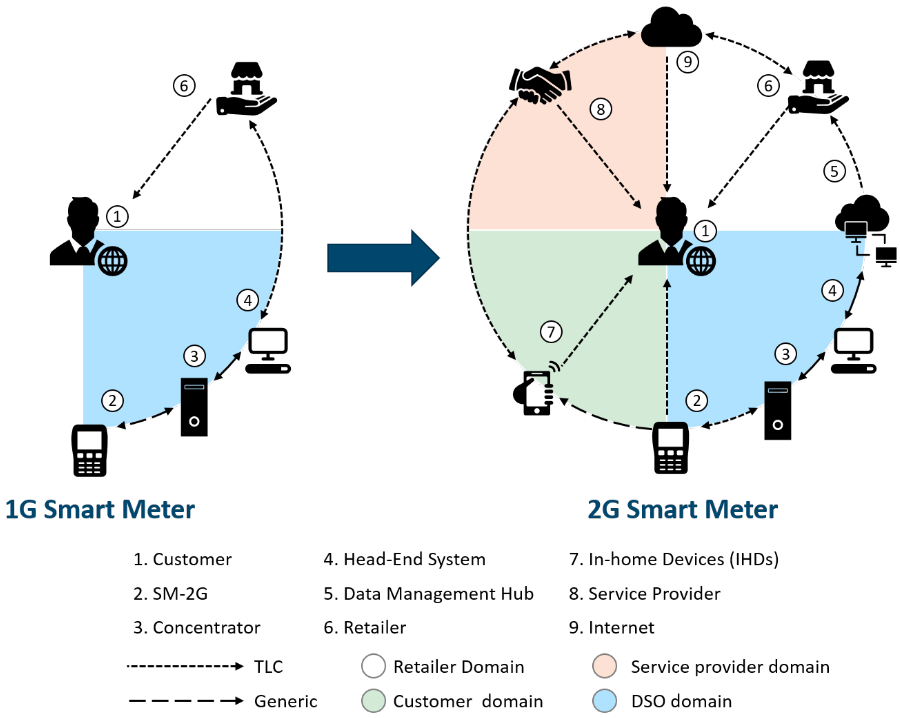



Fig. 1.7 Evolution of Smart Meters from 1G to 2G (based on Pitì et al. [220])

### 1.2.3 Harmonisation of 15-minute Settlement

The Electricity Balancing Guideline (EBGL Regulation) obliged all EU nations to switch to 15 minutes Imbalance Settlement Periods (ISPs) from the current popular ISPs of 30 and 60 minutes by December 2020 or January 2025 in the event of derogation (Kurevska et al. [161]). Currently in Europe, ISP of 60 minutes is most commonly being used, and 30 minute ISP is only popular in France, Ireland, and UK. The new move towards 15-minute settlement means that the current 1G smart meters should be changed to 2G smart meters on priority basis as smart meters must be able to record data with 15-minute time intervals. This 15-minute settlement also means that 1G smart meters are outdated and must be replaced with 2G smart meters. According to some regulatory authorities such as Ofgem, the movement towards ISP of 15-min would mean increased expenses as the current smart meters would need to be replaced and redesigned (Ofgem [206]).

Recently in May 2020, Ofgem performed a Cost-Benefit Analysis (CBA) for adopting the ISP of 15-minutes and found that the change to 15-minute ISP is not bringing them any significant benefits (Ofgem [204]). They found out that the implementation costs have even increased from what was initially proposed by original Frontier Economics CBA in 2016 (Economics [74]). The original CBA predicted that the movement towards 15-min ISP could negatively affect the UK customers. Ofgem's latest CBA findings also found that the move towards 15-min ISP would produce a net cost between -€615m to -€1,816.6m. On the basis of these latest findings (May 2020), Ofgem decided to grant a waiver of this duty to electricity system operators in the UK (Ofgem [206]). Another report by Empower in 2018 published a landscape for smooth transition to the 15-minute ISP (Empower [79]). They encouraged the energy market players to realise various phases and components involved in market designs of smart meters and their deployment. This would help in focused and targeted discussions among stakeholder groups and mixing of various problems would be prevented. Figure 1.8 shows the conceptual model for dividing up discussions into various phases.

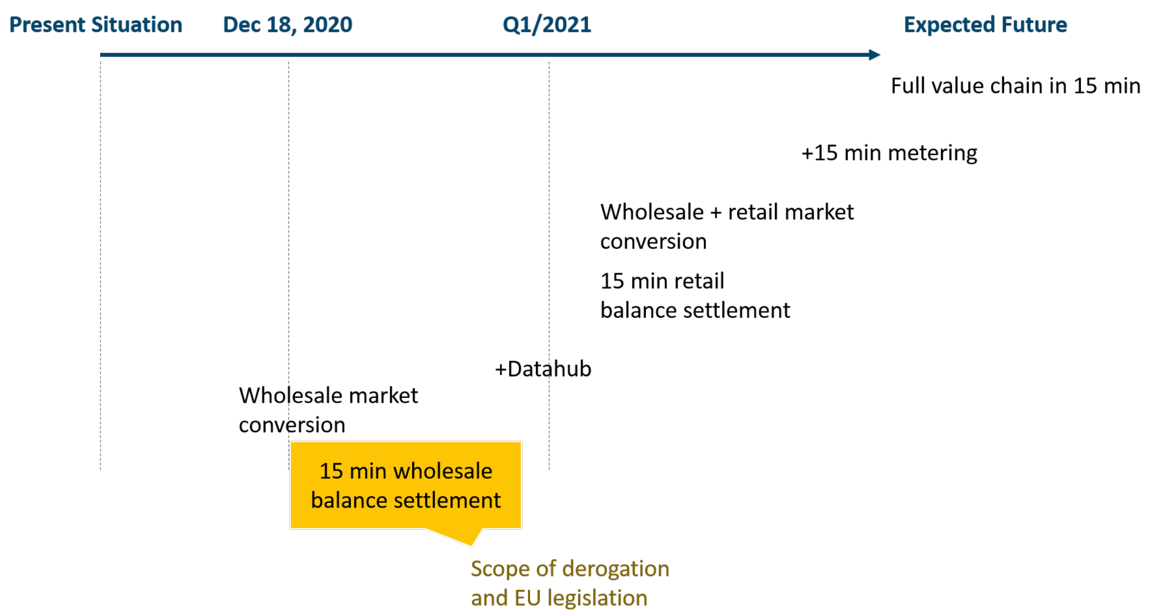



Fig. 1.8 Concept of smooth harmonisation of 15-min ISP (based on Empower [79])

### 1.2.4 Smart Meters Installations

Globally, the rise in the number of smart meters from 2013 to 2017 is shown in Figure 1.9, with the majority being in China followed by Europe and North America. China has already installed more than 513 million smart meters at the start of 2019, making up 64.3% of worldwide deployments. Western Europe installed 14.1% of global smart meters, and North America installed around 11.6% (Michael Kelly [186]). However, most of these smart meters are still using the concept of AMR, even though 2G smart meter employing AMI are also being deployed and are gaining popularity in countries such as Italy (Stagnaro [254]). Sweden and Italy have the world's oldest smart meters installed, but now they are updating them with the second generation.

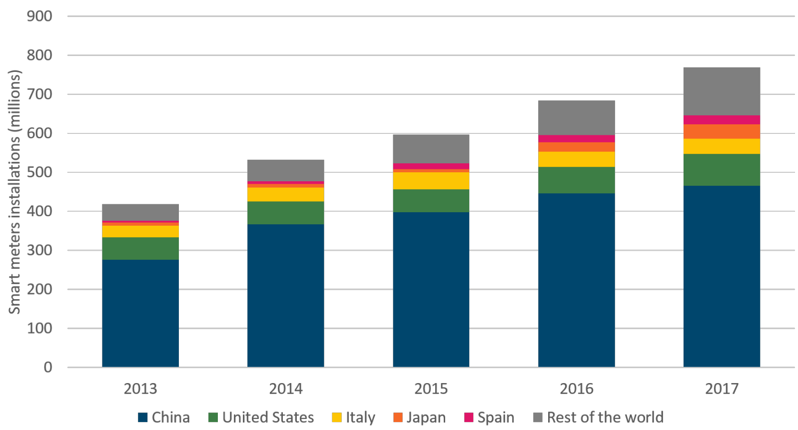



Fig. 1.9 Smart Meter installations across the globe (2013-2017) (based on [51])

Figure 1.10 depicts the present and forecasted number of smart meter installations as well as cumulative investment from 2017 to 2025, according to the latest report of AMI global forecast 2020-2025 (Mackenzie [176]). Over the next five years, utilities around the world are expected to spend about $30 billion to deploy 300 million smart meters, bringing many of the world's most densely populated nations to full implementation. However, many parts of the world will also be left with significantly lower adoption. It can be seen in Figure 1.10 that combined expenditure in AMI-based smart meters will grow to $127.6 billion in 2025 - increasing from $97.4 billion cumulative expenditure currently (2020).

From 2020 to 2025, total global smart meter installations are expected to grow from about 1 billion to almost 1.3 billion. By 2025, Asia will lead the global industry with approximately 40% of all the new meters installations, or over 136 million units. A total number of around 850 million smart meters will be deployed throughout Asia, with 640 million in China, 22.5 million in South Korea and 82 million in Japan. India will account for 300 million possible

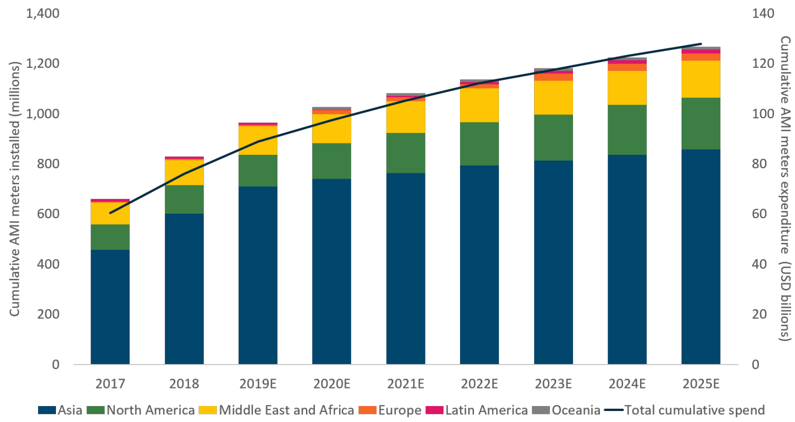



Fig. 1.10 Smart Meters installations and their expenditure around the world (2017-2025) (based on [176])

installations of smart meters, projected to be the second-largest industry after China, but has only installed around 7.7 million smart meters in 2019 (Mackenzie [176]).

Europe is expected to invest over $17 billion, or around $2.9 billion annually, installing over 110 million smart meters by 2025, as nations including Spain, France, UK, Netherlands, and others turn to full launch. According to (Mackenzie [176]) analyst, Netherlands, Spain, and France are likely to meet the EU target of deploying smart meters at the premises of 80% of all consumers by the end of 2020. The UK has claimed that it would reach this target by 2024. The smart meter roll-outs in Germany are slow because of cost issues and data privacy policies imposed by its government.

In North America, the U.S. utilities expect to invest almost $3 billion to install 24 million smart meters in addition to approximately 104 million smart meters already installed in this year. In 2025, about four-fifths of U.S. electrical companies' consumers will have smart meters, which will be a rise from around two-thirds as of the current year 2020. However, this projected time frame progress may halt if regulatory authorities postpone a substantial number of utility initiatives.

Finally, slower growth in Africa and Latin America is expected over the next five years. By 2025, less than one in five Latin American electricity users will have smart meters, regardless of major installations in Brazil and Mexico. Most of Africa stays without smart meters, though government of Egypt intends to install 30 million in the coming 10 years.

### 1.2.5 Industrial Smart Meter Analytics Applications

The growing penetration of smart meters allows collection of an enormous amount of fine-grained energy consumption data, thus a significant subject worldwide is how to utilise large amounts of smart meter data to improve demand-side efficiency. Retailers are no longer using smart meters only for billing purposes - they are using forecasting methods to boost their financial returns and enhance customer support. Detailed smart meter data is offering valuable insights into the consumer lifestyles and energy consumption patterns to compete with the growing competition in electricity market, making the retail sector more successful, productive and competitive (Yang et al. [300]). Moreover, DSOs are eager to use smart meter data analytics to improve network performance by effective system planning and outage management. More and more projects in the field of smart meter data analytics are also being built around the world.

Recently in 2017, SAS [238] issued a technical report that mentioned the findings of its industrial smart analytics survey (Figure 1.11). This study intended to identify the problems and patterns in the usage of data analytics by the utilities to meet their business objectives. About 136 electrical companies from 24 countries participated in the survey. The published findings showed that the main data analytics application fields include energy forecasting, smart meter analytics, asset management/analytics, grid operation, customer segmentation, energy trading, credit and collection, call centre analytics, energy efficiency (EE), demand response (DR) programme management, and DR marketing.

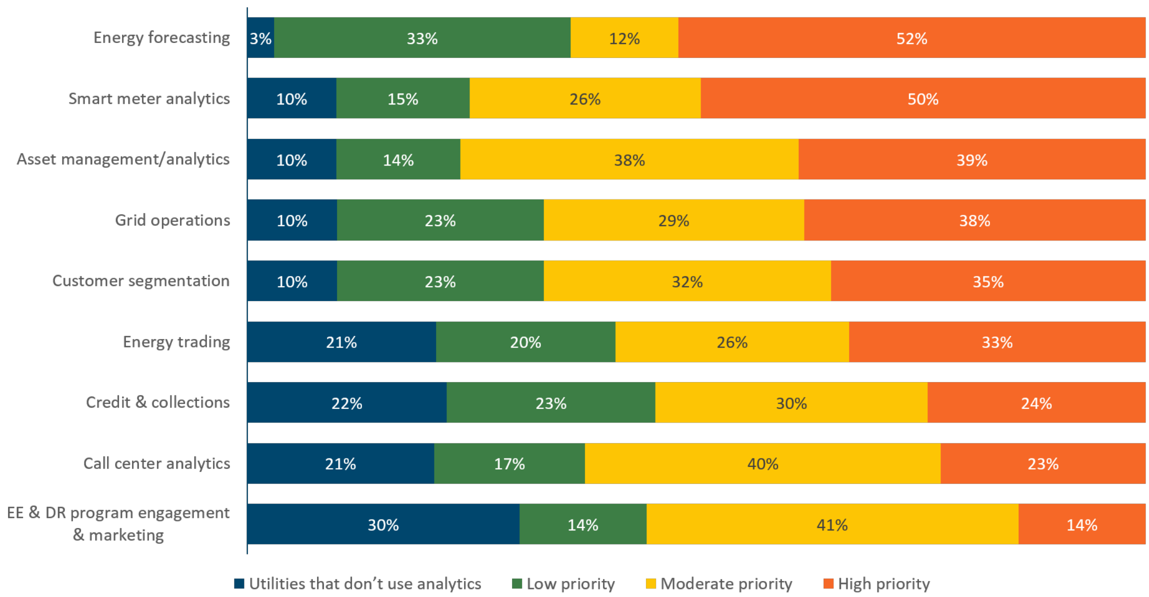



Fig. 1.11 Utility priorities percentage in Smart Analytics application areas (based on SAS [238])

Given the soaring demand for analysing millions of data collected via smart meters, increasing the number of energy data analysts will be an important challenge. This is addressed by a combination of commercial, public, and academic initiatives (Hong et al.

[127]). For instance, Energy Systems and Data Analytics MSc, a programme being offered by University College London, is teaching students how data analytics can be used in energy systems (UCL [273]). In Denmark,the CITIES Innovation Centre is supporting many projects that are inspecting the potential of machine learning algorithms to enhance load prediction accuracy and savings possibilities for consumers (Liu et al. [169]). A joint Research Centre of several universities, the Bits to Energy Lab, has also announced many initiatives for smart meter data analytics that are investigating occupancy detection, non-intrusive load monitoring, and base load estimation (Bits to Energy [27]).

Multiple start-ups are also utilising smart-meter data in their business models and technology to innovate in the sector. For instance, Opower was formed in 2007 to offer SaaS based customer engagement products to the electrical utilities. It provides software to utility companies that addresses a variety of smart meter data analysis application areas, including EE, DR, distributed energy resources (DER) management, call centre analytics, energy disaggregation, and dynamic segmentation and marketing (Opower [209]). Other examples of companies in operating in this space include Bidgley (Bidgely [26]), SMAP Energy (SMAP Energy Limited [250]), Eliq (Eliq [78]), and more.

While each startup can be differentiated in terms of technical speciality and geography, the use cases and values will frequently overlap. For the utility, these startups offer products that can add additional products and revenue streams, as well as opportunities for improving the customer relationship. Through digital EE and DER management applications, utilities can improve customer satisfaction and product uptake by offering streamlined consultations and personalised recommendations for a number of energy packages (home retrofits, solar panel installation, etc.). This also offers additional revenue streams for the utility in the form of product sales, as well as a path to "locking in" customers for longer term engagements - both critical advantages in competitive retail markets. Digital applications can also enable energy disaggregation - an approximate breakdown of consumer's total power consumption into identifiable groups, including cooling, heating, and illumination - which in turn can be used to identify the best consumer groups for issuing DR programmes and promoting the sales of products such as connected home devices. Moreover, through dynamic segmentation and marketing, utilities can quickly curate relevant customers and accelerate acceptance (up to 61 % more than standard marketing).

Such startups are often working closer to the consumer (demand side), where inefficiency remains and has been dramatically changing with the roll-out of smart meters. They are trying to unlock the value from smart meter data and give consumers and distributors information and value-added services for revenues. The next sub-section introduces the concept of

Demand Side Management (DSM), which is one of the major and promising application of smart meter data analysis that will be implemented in this thesis.

## 1.3 Demand Side Management

In energy system operation, there are two different practices that can be followed to meet the total forecasted energy demand: increasing the energy generation by bringing new physical energy resources at the supply-side and deploying responsive methods that can offer artificial resources at the demand-side. The first approach simply involves the building of additional generation resources to meet rising demand, and the second strategy offsets the growing load demand by formulating appropriate managerial actions that create virtual resources at demand-side by changing the power demand.

Clark W. Gellings invented the phrase ‘demand-side management’ in 1980s (Gellings [103]). Demand Side Management (DSM) is preparing, executing and tracking the utility operations such that the use of energy by consumers can be manipulated and adjustments in load magnitude and the time pattern can be achieved. Customers and utilities may handle the consumption pattern separately, but the DSM goal involves a utility/customer relationship which produces mutual benefits (Gellings [102]). In (Gellings et al. [104]), the purpose of DSM was limited to the design and execution of programmes that can actively shape the electric load profiles and obtain desired energy usage, fewer operating costs, and an economic stability. But since the 1990s, a number of theories, methodologies, and definitions have been presented in the literature to synchronise the fundamental conceptual framework of DSM with power system transformation. For example Goldman and Kito [110] examined the effect and experience of electrical companies with DSM bidding programmes. In addition, the concept (initially proposed by (Daryanian et al. [56])) of demand-side response has been commonly used by the researchers - for example, by Baladi et al. [21] and Roos and Lane [234]. After that, DSM responding to price became an interesting concept for research.

### 1.3.1 Classification of Demand Side Management

Palensky and Dietrich [210] classified DSM into the four types depending on the time and effect of the implemented steps at the demand side, also depicted in Figure 1.12:

1. Energy Efficiency (EE)
2. Time of Use (TOU)
3. Demand Response (DR)

4. Spinning Reserve (SR)

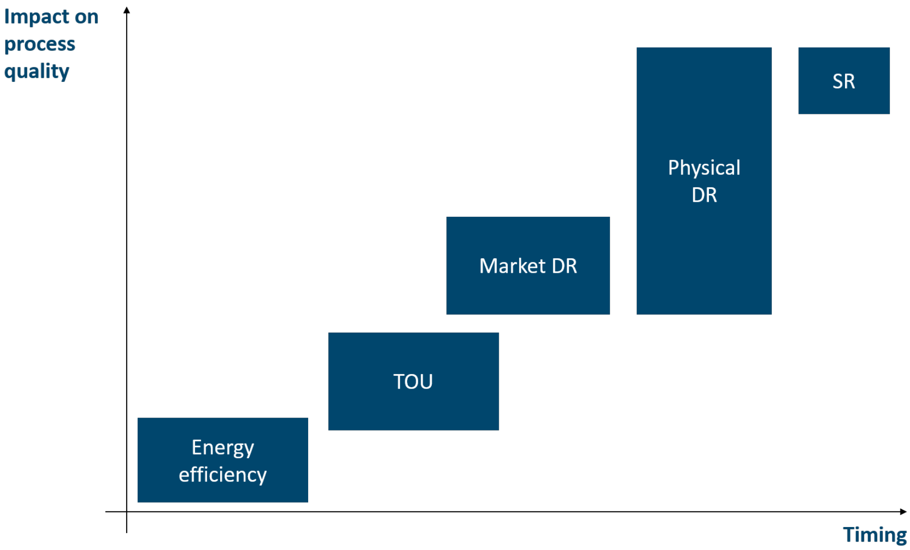



Fig. 1.12 Classification of Demand Side Management (based on Palensky and Dietrich [210])

EE methods - the first category of DSM spectrum - include all constant apparatus changes - for example, replacing an ineffective ventilation system with a more efficient one or making investments in the building structure through the inclusion of extra insulation. These steps have the benefit of saving energy and emissions immediately and permanently, and thus are the most popular tool. There is another term known as Energy Conservation, it can also be considered to belong to this category of DSM, as it relies on consumer changes in behaviour in order to accomplish better energy efficiency.

In the TOU category of DSM, the utilities define tariffs in such a way that the electricity price is high during some time intervals and low during the others, generally corresponding with times of higher or lower demand. For example, a utility may want its consumers to reduce consumption from 13:00 to 15:00, and it can achieve this target by setting high electricity prices during these hours. The expectation is that consumers will be discouraged to use more energy during this time interval and will reorganise their energy-consuming operations to lower-cost periods in order to reduce their electricity bills. Moreover, an alteration to the TOU fixed pricing plan would mean that a new contract needs to be signed between the utility and the consumers, thus, this does not take place frequently.

However, TOU may not automatically decrease overall energy consumption as certain energy consuming activities will continue to happen regardless. If a certain electronic appliance or system is changed, it may have to go back to its original state once the peak timings with high rates are over. For instance, a groundwater pumping device that can be quickly emptied for 30 minutes of peak period due to its reservoir tanks will refill the tanks after the period concludes. Therefore, a "rebounding impact" (or repayment) happens, energy is still consumed, and perhaps a new energy peak may emerge. This impact can be anticipated and possibly prevented with a combination of controls, predictive analytics, and rate design. TOU is further explained in detail in the next section.

DR – the third type of DSM – describes the “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” (DoE [67], Chiu et al. [46]). By facilitating consumer engagement and response, DR influences short-term effects on the energy sector, resulting in financial gains for both utilities and the consumers. It also decreases the total plant and capital costs by enhancing the efficiency of the power grid and in the long run reducing the peak load (Goldman [109]).

Consumers may take part directly in DR programmes through the utility, or can participate indirectly via an intermediary. In regulated markets, like wholesale power markets, smaller consumers are usually aggregated by intermediaries, referred as aggregators, curtailment service providers, or demand response providers that provide aggregated customer capabilities to the organised market (Chiu et al. [46]). If appropriate benefits are given to the consumers, they may organise their power consumption in order to minimise the peak to average demand ratio or mitigate power costs (Mohsenian-Rad et al. [190]). However, low consumer flexibility and practical circumstances which are inherent to the consumer can mean that actual load shedding for power system can be uneconomic and will produce diminishing returns when carried out through price incentive only .

There is a need to dedicate contractual demand management requests if the power grid or portions of its network (transformers, power lines, substations, etc.) are not performing as usual because of failure or maintenance (Palensky and Dietrich [210]). The last category of DSM, spinning reserves, addresses this (Palensky and Dietrich [211]). Spinning reserves refer to the first plan of a power grid operator to preserve grid stability after a major system failure, including unplanned failure of a large-scale power plant or an important transmission line. The DR spinning reserve projects function by aggregating separate controllable and small loads such as domestic appliances (Eto et al. [84]). Loads may function as a ‘virtual or negative’ spinning reserve if their power usage is related to the grid via smart means such as ’droop control’.

Spinning reserve is regarded both as the primary control, which says that active power output ultimately depends on frequency, and as secondary control, to maintain grid state and frequency with extra active power (Vasquez et al. [275]). This is usually the job of controlling power stations, but in simple terms loads will utilise less power if the frequency of the power system decreases. It can be done independently (such as primary control), or in a coordinated fashion (such as secondary control). Furthermore, loads managed by modern SCADA standards, such as IEC 61850 or central management and dispatch node, can also act like virtual storage through load changes. The combination of these loads results in total loads that can take part in energy markets and can keep up with standard power storage systems (Kirschen [155]).

### 1.3.2 Importance of Demand Side Management

DSM has a large potential to help in improving the power system efficiency and the use of available resources. According to Gellings [102], it could be used as a means of achieving various load shaping targets such as valley filling, peak clipping, strategic conservation, load shifting, flexible load shape, and strategic load growth depicted in Figure 1.13.

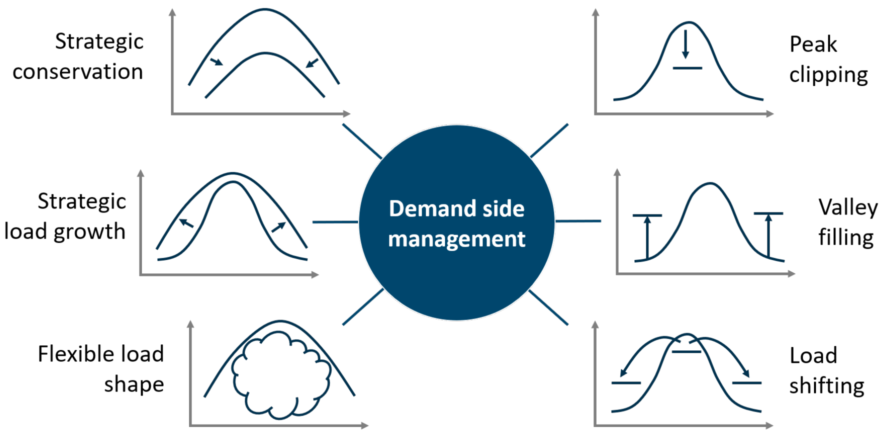



Fig. 1.13 Fundamental Load Shaping Methods (based on Gellings [102])

The mixture of the above methods allows the load curve to be as close as possible to electricity production curve. This might reduce the amount of resources required to meet customer demands utilising current generation methods (mostly fossil fuels) and could substantially boost the load factor (Strbac [256]). With more DSM installations, there may be a significant rise in the competitive pressure and reduction in the dominant generation stakeholder's "market power" (Rad et al. [227]). Reducing the influence of the market is an important primary concern for system operators (SO) in order to ensure favourable energy prices.

DSM also provides the option to deal with demand shortages without building costly new generation power plants. As new power systems incorporate greater contributions from renewable energy resources with high degrees of variability, DSM will be especially valuable. For instance, wind power plants could evidently match the large volume of energy produced by traditional fossil-fuel power plants. However, being dependent on the wind, the amount of energy being generated in real time can change quickly, presenting a challenge to ensuring the resilience of the grid.

DSM will also act as an alternate method of power reserve since a traditional standby power plant or another related approach would be possibly ineffective and expensive. Strbac [256] claimed that DSM may generally bring a wide range of advantages for network system, including: delaying investments for new network; enhancing distributed generation access to the current power distribution network structure; reducing challenges of voltage-constrained transmission of power; reducing heavy traffic in substations at the distribution side; optimising the handling of power outages; improving the productivity and energy security to critical customers; and producing a sharp decrease in emissions.

In summary, multiple forms of technology and coordination between the utilities and the consumers are required based on the categories of DSM. The latest introduction of smart metering devices in the domestic sector has attracted researchers around the world to look into how these can be fused with DSM programmes. TOU tariffs are an efficient substitute for flat tariffs as they offer customers with electricity price certainty for different hours throughout the day, in addition to not requiring additional infrastructure beyond the smart meter (Newsham and Bowker [196]). Therefore, TOU is one of the most common types of DSM programmes and holds a promising future (Hirst [124]).

## 1.4 Time-of-Use Tariff

Supporting domestic customers to shift the period during which they use energy is a crucial component of many government's decisions to make sure that regional supplies of energy are safe and sustainable in the move to greater penetration of sporadic renewable energy resources and the electrification of transport and heat (Carreiro et al. [38]). One method of encouraging customers to shift their consumption behaviour is by offering them monetary savings through time-of-use (TOU) energy tariffs, where electricity rates differ according to conditions such as the retail energy prices and the power network limitations. The literature shows that consumers would adjust their patterns of consumption in answer to a wide range of TOU prices. Cappers and Sheer [37] and Economics and First [75] have assessed 30 cases to show the effects of TOU tariffs on load demand.

There are several variations of TOU tariff structure and some of these tariff plans may be more attractive to consumers than others. Nicolson et al. [198] describes four main types of TOU tariffs (see also Figure 1.14):

- Static TOU pricing. In this scheme, there are multiple electricity rates throughout the day (or days), but their timing and amount are permanent and do not change. It is targeted to address large periods of time, typically on the order of months or years. For instance, utilities can announce peak pricing rates from 4 to 8 PM on weekdays, and lower rates at other hours. There can be numerous structures to accommodate seasons, day of the week, and time during the day, but in all cases the rates are pre-determined and the customers are informed many days in advance (Dupont et al. [71]).

- Real-time pricing (RTP). The price is dynamic in nature and offers variable real-time rates that may change throughout the day and according to the current wholesale price of energy. For example, utilities may calculate prices for the next 15, 30, or 60 minutes, but the crucial difference is that the advance notice time of RTP programs is usually less than a day (Dupont et al. [71]).

- Variable Peak pricing (VPP). VPP is a combination of static and dynamic electricity prices. The rates are fixed but their "window" of application fluctuates frequently. For instance, there can be high, medium, and low rate hours, and users will be informed in advance (e.g. less than a day earlier) the timings during which these rates will be applied.

- Critical peak pricing (CPP). In this type, high rate incidents are alerted to consumers in advance with notice of generally less than a day - similar to RTP programs - but the difference is that the rate is usually fixed (Dupont et al. [71]). The prices are usually high during those times of the year when wholesale electricity rates are high.

Though TOU electricity tariffs have long been the focus of grid management practices comprising many significant commercial and industrial users, residential TOU services remain limited to fairly elementary legacy choices such as the France Tempo Electricity Tariff (Crossley [53]), Great Britain Economy 7 tariffs (Focus [96]), and some states of the United States. The TOU pricing plans operated by Electricite de France EDF [76] are the highly effective examples of residential TOU pricing. It was estimated that 25 % of its 30 million consumers are using TOU pricing plans (Cousins et al. [52]). They announced voluntary pricing designs for domestic customers in 1965 after offering it to their industrial users in 1956. In the United States, more advanced TOU rates are now available on the market. Since 1978 in California, TOU tariffs were made compulsory for users consuming

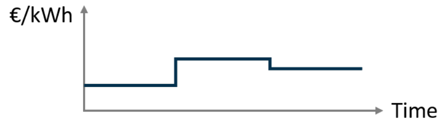
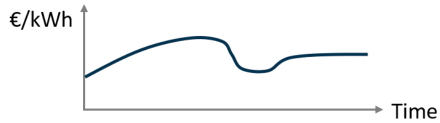
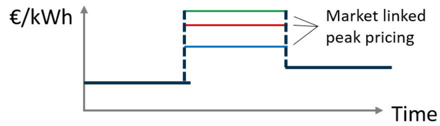
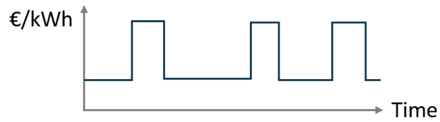
| Type of tariffs | Nature of pricing | Illustrative graphical representation |
|---|---|---|
| Static ToU pricing | Static |  |
| Real time pricing | Dynamic |  |
| Variable peak pricing | Combination of static and dynamic |  |
| Critical peak pricing | Combination of static and dynamic |  |

Fig. 1.14 Main types of Time-of-use Tariffs (based on BRIEF [32])

more than 500 kW to deal with the power crisis issues of 1973. Moreover, many utilities in different parts of US offer voluntary residential TOU prices. In literature, some more advanced works presented technological tools, generally smart thermostats, that could be configured by consumers in higher peak period price cycles to reduce their HVAC load set-points (Wang et al. [280]). These innovations can also help residential TOU tariffs to be more attractive.

### 1.4.1 Importance of Time-of-Use Tariffs

When correctly applied, time of use tariffs can greatly contribute to monetary savings for both the utility and consumers due to the shift in load demand. The projections of savings will differ according to the load size of the participant and the subsequent response to the pricing. Furthermore, the part of the population with a lower-than-average load curve might still see significant cost savings from such price plans, because some plans may be offering more incentives to customers with lower overall load.

According to Hledik et al. [125], there are also additional possible benefits of TOU tariffs which are not monetary but are vital for the both utilities and consumers. For example, it is hypothetically possible to convey price signals for ancillary services to domestic retail consumers and facilitate their participation. Ancillary services are mechanisms that enable grid operators to establish a stable power system. They may include services to mitigate the supply-demand energy imbalance, assist the power system in recovering after a failure, and keep the proper electricity flow.

Another benefit of TOU can be a reduction in wholesale electricity price. A decrease in load demand during peak load hours may reduce wholesale electricity prices temporarily – producing a gain for customers as energy costs reduce on the whole and allow net savings to be passed on. Further, the stability in price can enable lower overall costs as the risk premium associated with "peaky" load can be reduced.

TOU pricing also offers environmental benefits. Peak demand is typically supplied by fossil-fuel sources (Ofgem [200]), so if TOU tariffs reduce or shift peak power demand, the fossil-fuel sources would need to produce less power. This in turn would result in fewer emissions, generally leading to a net environmental gain. However, the impact on the environment of many of these TOU tariffs is very small, given the small number of peak price activities and minimal adjustments in overall consumption of electricity. Nonetheless, some research has indicated that TOU tariffs may contribute to a net decrease in overall energy consumption by promoting an enhanced awareness of energy consumption and mitigation activities (such as by encouraging the use of energy efficient devices) that carry over into more efficient lifestyle and consumer choices on the whole (Di Cosmo et al. [64]).

Moreover, TOU tariffs may enhance the economic appeal of many kinds of distributed energy sources, for example, electric vehicles, rooftop solar PV modules, and energy storage. Indeed, TOU tariffs are already vital for household owners if they plan to install PV units on their rooftops. The domestic PV power producers may receive payments for every kWh of energy that they produce. However, this payment may vary throughout the day. For example, the homeowners will get higher rates for sending power back to the grid during the peak time rather than sending it back during the off-peak hours. Furthermore, homeowners would also be able to reduce their energy bills by analysing the TOU rates and using more of the energy that they produce when these rates are high. The next sub-section discusses the relationship between domestic PV power producers and electricity tariffs in detail.

## 1.5 Domestic Feed-In Tariff (Solar)

Motivated by the pressing issues of climate change, increasing fossil fuel costs, and efforts of authorities to limit reliance on imported fuel internationally, governments are promoting the production of electricity using renewable electricity sources. Among the most popular sources of renewable energy, solar PV technology is growing rapidly with producing 59% of the total green energy worldwide as shown in Figure 1.15 in 2019 (Agency [4]).

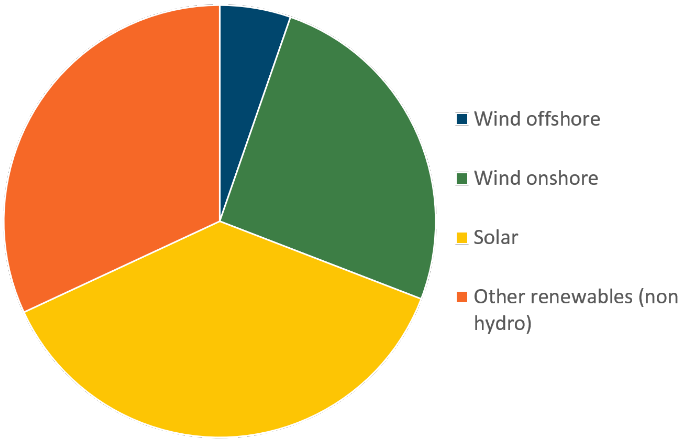



Fig. 1.15 Global electricity production from renewables installed in 2019 (based on Agency [4])

As a major aspect of the commitments of the governments across the world to handle the changing climate and energy security, a variety of economic incentives have been put into place to promote the use of renewable energy, and particularly solar PV. One such reward is a feed-in-tariff (FIT) plan, which attracts consumers by offering them valuable long-term contracts as discussed below.

### 1.5.1 Global Deployment of Rooftop PV

Solar photovoltaics have shown a strong domestic development over the past few years. Photovoltaic systems are widely known as advanced technologies for domestic usage and critical to meeting renewable energy deployment targets (Energy and Change [80]).

According to IEA [138], domestic solar PV production is expected to grow to 143 GW in 2024 from 58 GW in 2018, and the yearly capacity increase is likely to be tripled and reach more than 20 GW by 2024, as demonstrated in Figure 1.16. Chinese domestic PV growth is projected to increase significantly in contrast to its past six years. Spurred by the feed-in tariff schemes (IEA [137]), China will record the world's largest deployed residential PV-based power generation capacity by 2024. Feed-in tariff incentive schemes are ensuring rooftop PV homeowners a reliable income for all their energy production. By 2024, China will also be exceeding the domestic PV generation capacities of Japan, EU, and the US combined.

In Europe, Germany and the UK are among the biggest four solar PV markets (PV Magazine [224]). The UK ended all rooftop solar PV incentives on 31 March 2019, removing the previous feed-in tariff (FIT) programme with the new Smart Export Guarantee (SEG) scheme. Initiated in January 2020, this scheme requires all licensed power providers with over 150,000

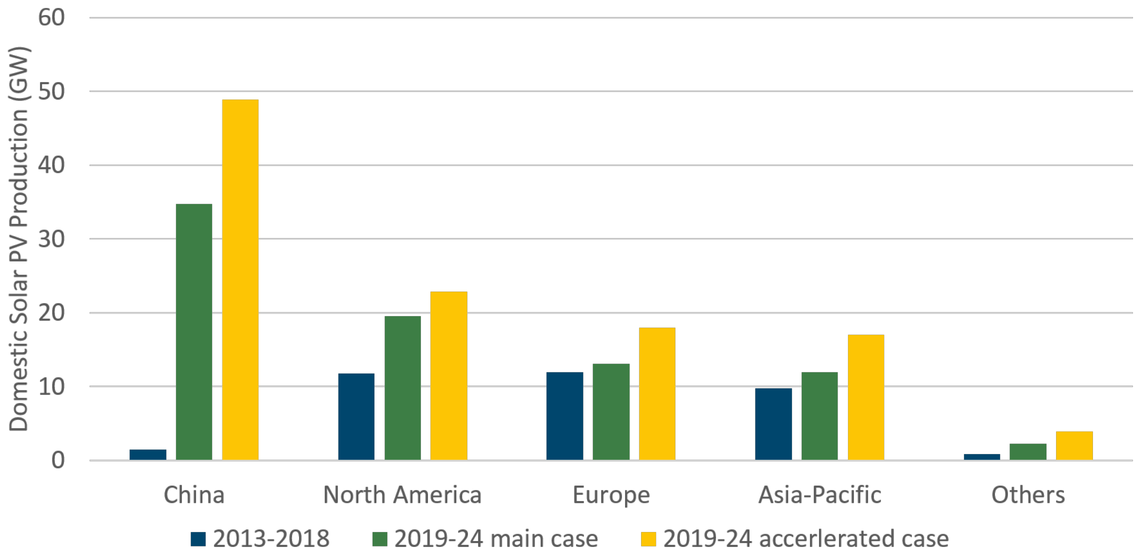



Fig. 1.16 Global capacity growth of domestic solar PV systems from 2013-2024 (based on IEA [138])

customers to give at least one SEG tariff to new domestic PV system installations. Smaller utilities can also provide a tariff if they wish. This termination of old FIT schemes did not affect the users which were already using it on their solar PV installations. In this SEG tariff scheme, the government does not recommend a particular tariff type, duration, or rate, but stated that the purchasing tariff must at all times provide an export rate above zero GBP per kWh, thereby providing income for domestic produces with excess solar energy. This is different from the previous FIT schemes where producers were paid a fixed rate for all energy they produced. The UK has about 3 GW capacity of domestic rooftop PV installations below 10 kW.

In Germany, 581 MW of solar PV projects up to 10 kW capacity and 3.9 GW overall solar projects were installed in 2019 [93]. Recently, German market research group EuPD Research reviewed over 1,000 householders and discovered that 20% of them are actively deciding to invest in solar PV. People surveyed said that they wanted to participate in PV installations to decrease their energy bills whilst contributing to environmental sustainability, and to gain from the government-guaranteed Feed-in Tariff schemes. Germany previously applied a 52 GW PV cap on the installations that would qualify for the incentive scheme, which EuPD Research proposed would be achieved by July 2020. After hitting this cap, no new PV system of less than 750 kW would qualify for the tariff plans, thereby threatening the further progress of PV development. However, the PV incentive cap was annulled by the government of Germany in May 2020, and now the commercial and residential PV sectors of the country await the introduction of a new criterion.

On the other hand, some nations, such as Greece and Italy, substituted their FITs with retail net energy metering (NEM) frameworks, which offer incentives to the power producers for the electricity that they provide to the grid. In NEM, the smart meter of the PV power producer runs in a backward direction when the user is exporting the surplus energy to the grid, and in a forward direction when the power production is not enough and the user is importing energy from the grid (Dan [54]). The utilities pay full retail electricity price to the PV power producers for the surplus power that they send to the grid, and if the consumption of the user is greater than the energy he is producing, he would buy energy from the utility.

Other nations, such as Portugal and Vietnam (Bridge [31]), have preferred self-consumption frameworks that work like NEM schemes but usually do not permit energy payment transfers. The common usage of smart meters has helped in removing the imbalance between consumption and generation by controlling these power flows in real-time. In self-consumption frameworks, the PV power producers use part or all of the power that their system is generating (Énergies [305]). This helps them in reducing electricity bills by avoiding having to pay full retail energy prices and associated charges. As an example of this, the standard retail electricity price in the UK is only 34% attributed to the wholesale cost of generation with the remainder attributed to grid charges, retail profit margin, VAT, and other items (Ofgem [205]). Assuming generation costs were equivalent, a consumer would be cutting 66% of the cost per kWh of electricity that they generate and use themselves.

Energy payment transfers are not involved when the user is using all of the produced power or is storing the excess, such as through a battery system. On the other hand, if the user is consuming only a part of the produced power and is importing the extra power to the grid, then the utilities can buy this power. However, this is not the main aim of self-consumption frameworks.

NEM schemes can have structural problems where they do not reflect the market price of electricity. For example, there are variants of NEM strategies (which are not true NEM schemes) and overall tariff allowances across the globe that pay customers below the actual retail price of electricity (Koumparou et al. [160]). In the Philippines, the Renewable Act of 2008 regulates the NEM strategies and the customers are often paid a generation cost that is even less than the half of the retail electricity price (The US Solar Institute [265]). Home solar PV customers need to sell the generated energy above levelised cost of energy (LCOE) to have a positive net present value (NPV) (Comello et al. [48]). The main challenge is to gain a positive NPV or grid parity as a reward.

### 1.5.2 Domestic Feed-in Tariff

A feed-in tariff is a strategic plan designed to speed up investment in renewable technologies by providing renewable energy suppliers with long-term agreements. The goal of the tariff is to provide green energy suppliers with cost-based incentives, long-term deals, and price certainty that indirectly assist funding investments in renewable energy. The tariff can apply to a series of technologies, such as, Anaerobic Digestion (AD), Wind, Hydro, and Photovoltaic up to a certain maximum total installed capacity. The core objective is to reduce the cost of such systems by offering a more secure return on investment. The term Domestic Feed-in Tariff (D-FIT) refers to the financial rewards offered to householders if they invest in renewable energy technology such as solar PV.

Let's take an example to better understand how the D-FIT scheme may help at domestic level. At the domestic level, a house owner will be reluctant to take the initiative of producing green electricity because it will be very costly up front to install a system - often in the thousands of pounds - and they have no guarantee that there will be a buyer for their excess energy at a price that makes the return on investment attractive.

As such, some may still consider the installation but will discount the return made from selling generated energy and select a smaller installation scaled to suit their own needs (in essence, a self-consumption arrangement). However, if they can be assured of the price their generated energy can be sold at, some may be convinced to opt for a larger system. This price assurance can be achieved through a D-FIT scheme in which the government regulator may force the utility or system operator to purchase electricity produced from renewable energy at a higher rate than the standard electricity price - sometimes by paying the difference from additional taxes or levies - to incentivise the deployment of renewables. As a result, more homeowners will now consider installing a solar PV system because the anticipated savings from the price difference will be both significant enough to pay off the system investment and assured as it is backed by the government.

The government may subdivide the applicants into small and large installation categories with different different FIT schemes, and the focus of this section is domestic PV installations (stand alone or roof mounted installations). The D-FIT schemes can be of the following three types:

1. Export tariff. In this scheme, each homeowner is provided with an extra fixed rate for each power supply unit that they add into the grid system.

2. Generation tariff. In the generation tariff, the homeowners are paid for both exporting renewable power to the main grid or using it themselves; this is unlike the export tariff, where homeowners are paid only for exporting renewable power to the grid. The

electricity provider will charge a flat rate for each generated power supply unit (kWh) and the price level depends on the renewable energy technology and the capacity of the installed network (Ofgem [207]). Once the homeowner registers, tariff rates are assured and linked with inflation rate.

3. Electricity bill savings. If the homeowners will be producing their own green electricity, they will need less power from the grid. As the renewable energy generated is also less expensive than the grid electricity, overall there will be a reduction in electricity bills.

Export tariffs are the most popular form of residential solar subsidies to make the investment lucrative for a homeowners. Any surplus energy that their solar PV energy production system contributes to the grid station is paid per kWh and is rewarded as an additional credit on energy bills. Recently a combination of TOU and DFITs is being offered by the retailers such as in Australia (Australia [19]). Previously, homeowners with PV modules could only sell back their surplus energy at a flat rate throughout the day, but with TOU/DFITs, varying rates during different time of the days are offered to homeowners. For example, if homeowners choose to go for TOU/DFITs, they may get higher payments for producing surplus energy during the peak hours rather than the off-peak hours. The homeowners could gain more benefits from such schemes by limiting their residential power consumption during the peak hours such that they have more energy to contribute to the grid station.

### 1.5.3 Decentralisation with Rooftop Solar PV

Domestic solar PV installations are now a central focus of the new energy system created by smart meters, communications, and two-way flow of power. The advent of this distributed energy resource and others such as plug-in EVs, micro wind turbines, and smart home appliances have made homeowners active members of the power system. As discussed in section 1.5.1, there are self-consumption schemes in some countries that permit homeowners to produce electricity for their own needs rather than getting a payment for supplying it to the grid. Therefore, the most profitable and optimal way to consume the self-produced solar power will include a more sophisticated smart homes system incorporating solar power with energy storage, PV systems, heating, electric vehicles (EV) charging, energy efficiency, and demand response (magazine [177]).

With DR programmes, homes with rooftop solar PV installations can be flexibly controlled based on the needs of the grid. Demand response is a process that allows users to adjust their energy consumption habits and provide grid services, either independently or via an aggregator. The homeowners with rooftop solar installations can produce, trade, consume, and store power, thus moving from being passive to active consumers, also called as prosumers (IRENA [140]). They now have more control over electricity production, and are altering the energy market dynamics with the versatility of demand-side management.

Rooftop solar PV installations along with demand response are contributing towards decentralisation of the power system. Optimising domestic electricity consumption can give the energy system cost-effective flexibility. However, customers will be more likely to openly participate in decision-making when as the financial rewards become greater and more certain, and consumer service options such as demand response are a necessity for enabling this.

## 1.6 Thesis Aims

The main aim of this thesis is to investigate opportunities and problems related to time-of-use tariffs at the national level utilising smart meter data. As of today, there exists a large body of research on smart meter data analytics and smart meter penetration has reached high levels in many developed countries. However, several points which prevent utility companies from practically implementing TOU tariffs at a large scale remain untouched, and the actual usage of these new technologies for DSM is still limited. Therefore, more practical modelling frameworks, which can bridge a large number of existing modelling works and commercial objectives led by utilities, has a vital importance. Major research gaps which need to be filled in order to expand commercial applications of TOU tariffs are identified with some practical solutions proposed in this thesis. The overall structure of this thesis and a description of each chapter is presented below.

Chapter 2 reviews existing academic literature relevant to a TOU tariff implementation and examines any gaps to preventing the large scale roll-out of the TOU tariff. This chapter identified four research gaps:"TOU load forecasting problem", "TOU winner detection problem", "TOU public dataset problem", and "excess generation forecasting problem". Each problem is addressed in the following chapters.

Chapter 3 describes "TOU load forecasting problem", proposing a top-down statistical medium-term load forecasting model of residential customer demand response following the adoption of a time-of-use tariff and reports the model's accuracy and the feature importance. The importance of statistical moments to capture various lifestyle constraints based on smart meter data, which enables this model to be agnostic about household characteristics, is discussed. 646 households in Ireland during pre/post-intervention of the time-of-use tariff is used for validation. The value of Mean Absolute Percentage Error in forecasting average load for a group of households with the investigated Random Forest method is 2.05% for the weekday and 1.48% for the weekday peak time. The content of Chapter 3 is based on the published work in the journal *Energy* [152].

Chapter 4 addresses "TOU winner detection problem", providing a statistical model to identify the characteristics of so-called winners and losers - or households that would be better or worse off under a TOU tariff, using only ex ante information. The results indicate that the model accuracy reaches a reliable level using historical electricity load and basic household characteristics as inputs. This accuracy can be further improved if customers' online engagement preferences are available - providing justification for the development of online interaction and gamification components in TOU programmes. This chapter (detailed in Appendix A) also makes a contribution to addressing the "TOU public dataset problem" by publishing a new public dataset (CAMSL) of 1423 households in Tokyo, Japan, including historical smart meter data, household characteristics, and online activity variables during the 2 years of comprehensive TOU intervention period in 2017 and 2018. The content of Chapter 4 is based on the published work in the journal *Energy* [153].

Chapter 5 presents the "excess generation forecasting problem", demonstrating a data-driven modelling framework to predict excess electricity generation, factoring intermittent generation, and customer load adaptation. An illustrative study, with a-year long dataset from 287 households in Tokyo Japan, is used to derive the forecasting model. Results show that year-long data from 18 households is sufficient for accurate prediction of excess generation across a uniform geographic and socio-economic setting. The content of Chapter 5 is based on the published work in the International Building Performance Association Conference (IBPSA2015).

Chapter 6 draws out conclusions and limitations of this research, then outlines possible avenues for future improvements and policy implications in smart meter data application and demand side management.

These chapters are modified from the published version in order to fit with the thesis structure. Note that the introduction and the literature review are kept in each analysis chapter, and some readers might feel this to be redundant where there is overlap with the previous chapters. The author however believe that keeping the succinct overview of holistic problems and relevant literature is beneficial for a wider audience (who might not have enough time to read through the entire thesis).

# Chapter 2

# Literature Review

## 2.1 Survey of Smart Meter Data Analytics Literature

Data analytics practices and case studies are now more prevalent in modern power systems. Motivated by the advancements in communication and information technologies, an information layer has now been introduced into the traditional power transmission and distribution system for gathering, storing, analysing the data. All of this is possible by utilising widely installed smart meters and sensors.

Wang et al. [281] work is the one of the latest and comprehensive review of smart meter data analytics applications. They carried out a bibliographic evaluation using Web of Science (WoS) databases to give an idea about the current research works in the field of smart meter data analytics. The terms used for finding relevant research papers were such as “consumption” or ”smart meter” or ”load” or ”demand” and ”data” and ”residential” or ”household” or ”resident” or ”industrial” or ”building” or ”individual” or "consumer” or "customer” and "demand response” or “energy theft” or ”forecasting” or ”clustering” or ”profiling” or ”classification” or "anomaly” and ”power system” or ”smart grid”. Figure 2.1 indicates the volume of WoS indexed publications from 2010 to 2017. According to Wang et al. [281], a total of 200 publications have been published in the field of smart meter data analytics in WoS by 2017. The number of papers before 2011 was reasonably small, and it steadily increased from 2012 and in the year 2017, it hit 60 in WoS. This outcome was as expected as the projects of smart grids mainly began in the late 2000s and the researchers required several years to acquire data for detailed testing and several more years to report and publish the results in journals.

In Wang’s work, the taxonomy of smart meter data analytics are defined in the following categories: load analysis, load forecasting, load management, and others. (see Figure 2.2):

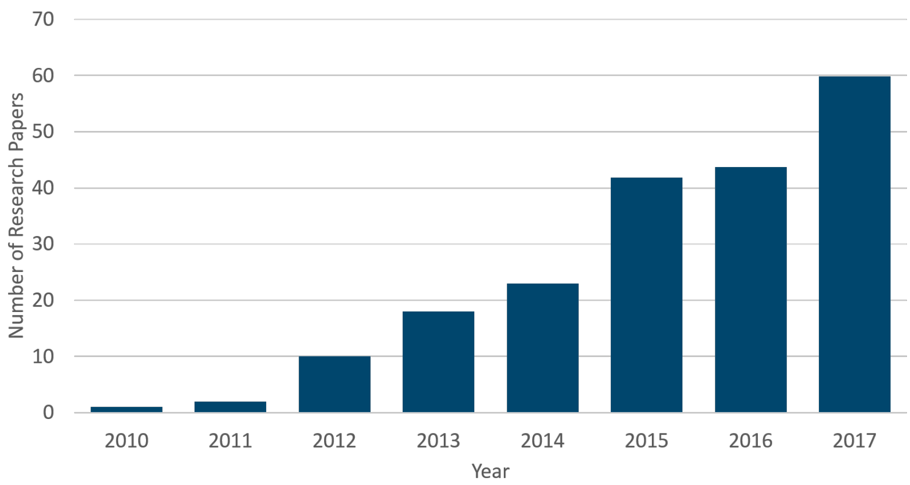



Fig. 2.1 Publications indexed by Web of Science from 2010 to 2017 (based on Wang et al. [281])

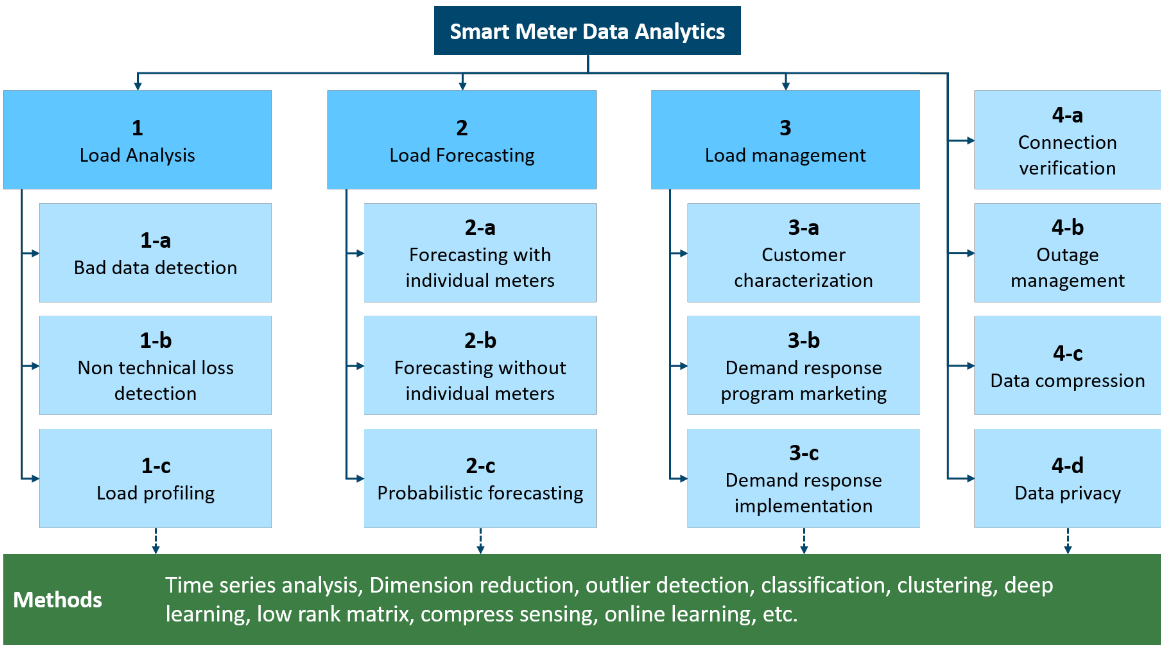



Fig. 2.2 Classification of Smart Meter Data Analytics (based on Wang et al. [281])

The load analysis category has been further divided into bad data detection, non-technical loss detection, and load profiling. In load forecasting, load forecasting with and without individual meters and probabilistic forecasting are included. The load management category is comprised of characterisation of customers, demand response marketing, and demand response implementation. The others section includes a combination of connection verification, outage management, data compression, and data privacy. In all these categories, the key machine learning methods that were utilised for smart meter data analysis include classification, clustering, dimensionality reduction, time series, deep learning, outlier detection, online learning, compressed sensing, low-rank matrix, and others.

Under this taxonomy, the existing academic literature relevant to the main aim of this thesis is mainly covered by two main pillars of "load forecasting" and "load management". A large number of existing literature studies under these two categories have been found, but the issues they cover are different from a traditional load forecasting problems in that customer behavioural adaptation under different TOU tariffs needs to be incorporated in forecasting models. This chapter reviews existing academic literature under these two categories and critically examines any gaps to prevent the large scale roll-out of a TOU tariff.

## 2.2 Load Forecasting

Smart meters allow electricity retailers and local utilities to properly understand and predict the power consumption of an individual building or house. Therefore, the load data supplied by smart meters have high spatial resolution that has the potential to significantly improve the forecasting performance. Since residential and building energy consumption could be more unpredictable and random than aggregated consumption, the conventional methods and techniques built for aggregate load forecasting may or may not be sufficient. Researchers are developing various strategies to deal with the challenges of the smart meter based load forecasting, such as assessing and changing the current load prediction methods as well as introducing new techniques. Figure 2.3 shows the different types of load forecasting based on geography and time resolution.

For the operation and control of a power system, accurate models for load or demand forecasting are vital. Load forecasts assist electric utilities significantly on decisions related to the generation and purchase of power, the growth of the power network, load switching, and more. The power demand depends on multiple parameters such as time, weather, and economic limitations. Load forecasting takes these variables into account and is helping utilities to play a part in the decentralisation of the power market.

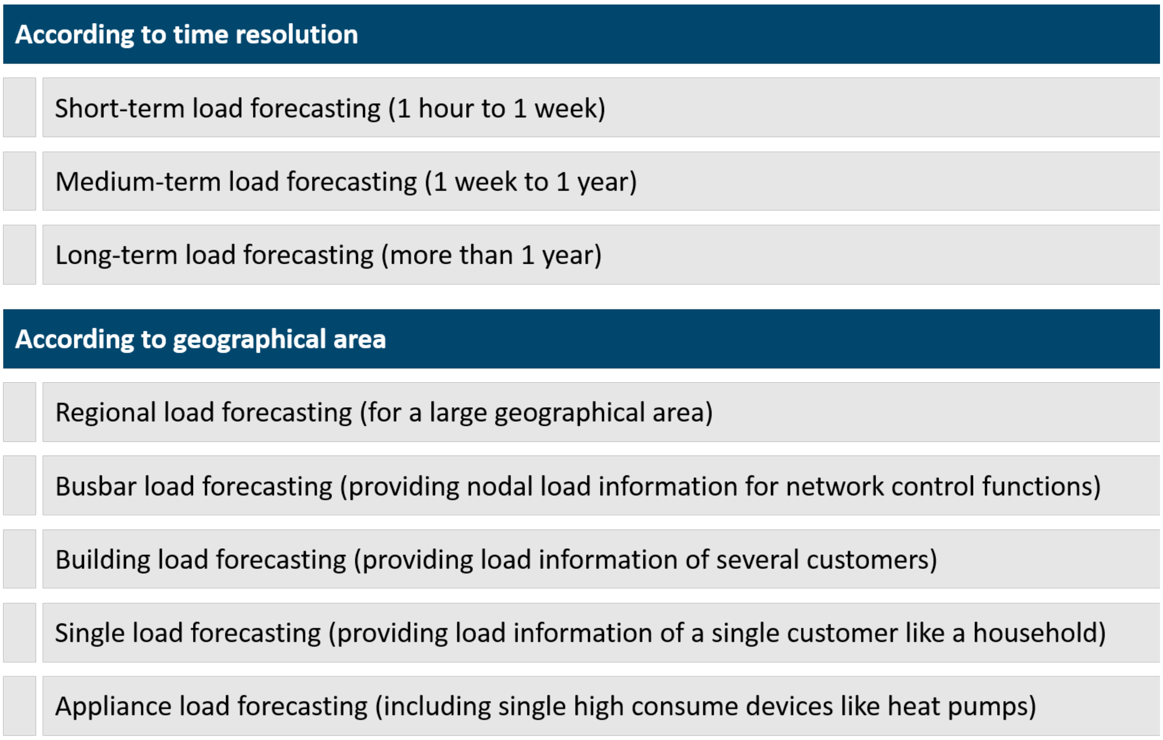



Fig. 2.3 Types of load forecasting based on geography and time resolutions (based on Estebsari and Rajabi [83])

Residential load can fluctuate very quickly as home appliances are turned on and off. Although the system-wide load prediction benefits from the load smoothing effect of several homes, rapid variations at each household scale cannot be prevented, making this load forecast more difficult. Moreover, rooftop PV installations at the domestic level need to incorporate these fluctuations in order to optimise home self-sufficiency and reduce the afternoon detrimental impact of PV excess generation on the grid (Weniger et al. [292]). The afternoon PV excess generation forecasting is also crucial as many countries have to reach their specific target of total domestic PV installed capacity.

Until the latest introduction of smart meters, high-resolution household data was lacking. Figure 2.4 shows the typical steps involved in a load forecasting model (LFM) using smart meter data. This section inspects how such LFMs have been developed in the literature based on the following research questions:

1. How to remove or incorporate the weather influences? In Figure 2.4, it can be seen that after selecting a particular application of load forecasting, the next step (2nd step) involves acquiring historical data for load, weather, and other variables affecting the load. Therefore, this research question deals with how researchers have been adding or removing weather variables at this stage.

2. What are the latest machine learning (ML) models for short-, medium-, and long-term load forecasting? Choosing the right forecasting model (step 5 in Figure 2.4) is critical for utilities, and continuous research is going on for finding an accurate, fast, and easy-to-use machine learning forecasting model. To answer this question, extensive research has been performed to find out the latest ML models that are being used according to various applications of load forecasts.

3. What are the popular input features for short-, medium-, and long-term load forecasting models? This also addresses the 2nd step of LFM depicted in Figure 2.4. The selection of input predictor variables highly depends upon the duration of load forecasting. Hence, subsection 2.2.3 discusses in detail what kind of features are being used in literature to forecast load on a short-, medium-, and long- term basis.

4. What are the popular methods for evaluating forecasts? Finally, it is obviously vital to assess the performance of different LFMs in order to choose the best one. Thus, subsection 2.2.4 deals with the last step of LFM and summarises the common performance metrics that are being used in literature.

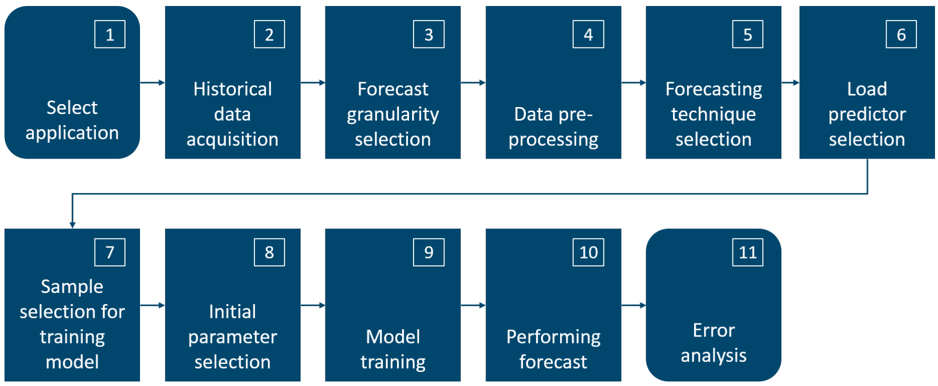



Fig. 2.4 Development of a typical load forecasting model (based on Lusis et al. [173])

### 2.2.1 Weather Influences

Weather influences can be highly important for domestic electricity demand (Beccali et al. [22]). This thesis has focused on how temperature influences can be removed or incorporated into the load forecasting models. It is vital to note that temperature influences on demand data decreases with time, therefore, these influences are usually not considered for medium- and long-term forecasting. They are only appropriate for short-term load forecasting up to a week. Based on literature, the following are the four popular ways of incorporating or removing temperature dependencies (Gan et al. [101], Gaillard et al. [99], Xie and Hong [296], Yu et al. [303]):

1. **Min-max scaler**. In machine learning models, the input predictor variables must be normalised to the same scale to comply with the scaling sensitivity of the neural networks. Therefore, the temperature data can be normalised using the popular method of min-max scaler defined by Equation 2.1:

$$T_{\text{norm}} = \frac{T - T_{\min}}{T_{\max} - T_{\min}} \tag{2.1}$$

   where $T_{\text{norm}}$ corresponds to the temperature normalised value, and $T_{\min}$ and $T_{\max}$ represent the highest and lowest temperature values in the specific raw data. The normalised temperature values will lie between 0 and 1.

2. **Exponential Smoothing**. It is a method for smoothing data, which must be time-series, using an exponential frame. In the traditional moving average method, the previous data points are assigned the same weights, but in exponential smoothing, an exponential parameter allots exponentially decreasing weights to the data with time. For smoothing temperature values and removing any arbitrary variations, the induction 2.2 can be used at any time $t$.

$$T_t^{(\gamma)} \triangleq \gamma T_{t-1}^{(\gamma)} + (1-\gamma)T_t \tag{2.2}$$

   where $\gamma$ is the exponential smoothing parameter ranging from 0 to 1, i.e., $\gamma \in [0, 1]$, $T_t^{(\gamma)}$ is the smoothed temperature, and $T_t$ is the raw temperature value that must be smoothed.

3. **Bootstrap method**. This technique first makes equal duration (hours, day, or years) fragments of historical temperature series data, and afterwards, it arbitrarily selects the fragments by replacing it with any other historical data to develop a new series of temperature data. This will assist in developing a comprehensive temperature scenario, but in the case of probabilistic load forecast, it may not result in a good quantile score.

4. **Cubic polynomial**. Let's assume $x$ is an input sequence of hourly load data with time length $Z$, and $\tau$ is the equivalent temperature vector with the same length. The temperature dependencies can be well-estimated using a cubic polynomial function defined by 2.3:

$$\underset{c_0,c_1,c_2,c_3}{\operatorname{argmin}} \frac{1}{2} \sum_{i=1}^{Z} \left(x_i - \left(c_3\tau_i^3 + c_2\tau_i^2 + c_1\tau_i + c_0\right)\right)^2 \tag{2.3}$$

where $c_0, c_1, c_2, c_3$, are the approximated coefficients and the temperature component of electricity demand is denoted by 2.4:

$$b(\tau) = c_3\tau^3 + c_2\tau^2 + c_1\tau + c_0 \tag{2.4}$$

where $b(\tau)$ shows that the cubic polynomial is applied element-wise to the temperature values vector $\tau$ . If temperature predictions $\tilde{\tau}_{Z+1}, \tilde{\tau}_{Z+2}, \ldots$ are available, then the cubic polynomial can be simply used to forecast the electricity demand $x_{Z+j}$.

### 2.2.2 Machine Learning Forecasting Models

Machine learning forecasting models are assisting in improving the performance of the whole power network, and the race is on to find the best of the best models for an accurate short-, medium-, and long-term load forecasting. This section discusses the latest machine learning models for load forecasting that are surpassing the existing state-of-the-art models. The next sub-sections discuss the ML models for short-, medium-, and long- term forecasting and Table 2.1 illustrates the ML models that have performed best for each category. The last two sub-sections discuss the emerging approach of probabilistic load forecasting in contrast to the point-based prediction and excess generation forecasting.

#### Short-term Load Forecasting

Short term load forecasting is becoming increasingly important as the energy generation market has deregulated and renewable resources have been aggregated. It includes predicting load for time intervals ranging from a few minutes to up to one week, and it is becoming particularly crucial for power market spot price calculation and bidding. However, the short-term load forecasting efficiency based on conventional algorithms is often unsatisfactory and not stable enough. Thus, various approaches have been proposed to improve the models' accuracy as well as introducing emerging techniques from deep learning.

A widely cited research paper of Edwards et al. [77] implemented and tested the performance of seven machine learning algorithms for predicting the residential power consumption for the next hour. They developed variants of support vector machines (SVM), linear regression (LR), artificial neural networks (ANNs), hybrid of fuzzy C-Means and ANN, hybrid of hierarchical mixture of experts (HME) and ANN, and hybrid of HME and LR experts. The test case was conducted on the basis of two datasets: one with two office buildings and another with three residential buildings. The study showed that the methods could not produce good predictions for the three residential buildings but performed well for the two commercial buildings.

This body of research often use clustering methods to classify meters with similar patterns to avoid the important features from being lost during aggregation. A clustering algorithm can first group the consumers, and then the load of every consumer group can be predicted using separate forecasting models. Eventually, the separate load predictions of every consumer group can be combined to obtain the aggregated load prediction and improve forecasting accuracy. For instance, Chaouch [41] developed the load forecast for the next day as a realistic time series problem. Initially, clustering was done to divide the historical load segments into various groups. At the end, functional wavelet-kernel based on clustering (CFWK) method was utilised to predict the next-day target segment. The results of daily median absolute error (DMAE) performance metric proved the effectiveness of CFWK when compared with simple FWK.

In addition, a Ward's linkage load modelling method based on clustering was also utilised in (Hsiao [131]) to predict the load patterns with 30 minutes forecasting horizon. In their work, clustering was done using contextual data comprising temperature, data, time, and economic parameters. The proposed approach outperformed traditional methods of SVR, LR, random walk (RW), back-propagation ANN, and auto regressive integrated moving average (ARIMA).

Other examples include Least Squares Support Vector Machines (LS-SVM), which was developed in (Edwards et al. [77]) for forecasting residential and commercial demand for the next-hour. The LS-SVM differs from the standard SVM approach in two ways. Firstly, its criterion function is based on least squares. This is a benefit as quadratic programming is not required for solving the objective function. The LS-SVM needs to only compute linear equations, and thus can quickly find solutions. Secondly, it has equality problem constraints rather than inequality ones. Nonetheless, LS-SVM does not have the SVM's sparsity property as it utilises all the data points to find a solution, but this may or may not influence its ability to form a generalised forecasting model. The proposed LS-SVM model outperformed HME variants, FFNN, and FCM with FFNN models when forecasting residential load.

In contrast to these works using classical machine learning techniques, the recent advancement in deep learning has introduced a new paradigm to boost the accuracy of the models in short-term load forecasting. The research work of Hong et al. [129] provides a technique based on iterative ResBlock and deep neural networks to learn the spatio-temporal relationships present in the load data of the appliances. ResBlock's simple framework contains two main components: one skip connection and a number of stacked layers. There are few hidden layers present in the stacked layers and end-to-end layers are linked directly. This framework is analogous to the ResNet He et al. [120] building block that is utilised for image classification, however, with a slight change. The authors tested their residential short-term load forecast model on real data and found that both the iterative ResBlocks and load data of appliances assisted in enhancing the prediction performance. MAPE, root mean squared error (RMSE), and mean absolute error (MAE) were reduced by up to 32.78%, 20% and 22.58%, respectively.

Moreover, self-Recurrent Wavelet Neural Network (SRWNN) was proposed in (Chitsaz et al. [45]) for forecasting 24-hour ahead load with prediction steps of an hour. The purpose was to handle the volatile and non-smooth power demand time series data in microgrids. The Levenberg-Marquardt (LM) algorithm was used to optimise the parameters of SRWNN during training. The proposed model was compared with simple WNN and normalised MAPE and RMSE performance metrics were used. The SRWNN model produced more accurate predictions with volatile load data than conventional approaches and showed lower values of RMSE and MAPE.

Very recently, a deep Bi-LSTM based sequence to sequence regression approach was proposed in (Mughees et al. [194]) for forecasting day-ahead peak load of a residential area both on special and normal days. The proposed six-layered deep Bi-LSTM forecasting model was compared with its shallow version, LM back propagation based ANN, Medium Gaussian SVR, shallow LSTM sequence to sequence, and deep LSTM sequence to sequence forecasting models. The results demonstrated that the deep Bi-LSTM sequence to sequence model performed better than the comparison models both on special and normal days. The load profile on special days (holidays) always differ from normal days and less data is available to forecast its load. This research work was successfully able to address the challenge of accurately forecasting load on such days.

The latest stochastic deep learning models, Factored Conditional Restricted Boltzmann Machine (FCRBM) and simple CRBM, were investigated in (Mocanu et al. [187]) for forecasting short-, mid-, and long-term power consumption. CRBM method is an improvement of RBM model as it has an additional conditional history layer. It takes in account all the potential links between weights, neurons, and biases when calculating the overall energy function. Similarly, FCRBMs are an improvement of CRBMs as it has two more layers namely features and styles. However, these layers can be reduced to a single layer to fit the forecasting needs. The results showed that FCRBM surpassed conventional machine learning models such as ARIMA, CRBM, HWM, ANN, SVM, and even surpassed some deep learning models such as RNN forecasting models.

### Medium-term Load Forecasting

Medium-term electrical load forecasting has become critical given the extreme impact of climate change on power consumption, as well as the latest developments in smart grids including the utilisation of renewable resources. Specifically, electricity pricing setting, grid maintenance planning, and energy distribution preparations all require medium-term load forecasts. It includes forecasting load for 1 week to up to several months, though the time interval must be less than a year. The authors in Shirzadi et al. [249] develop and analyse ML models for medium term load forecasting. Upon completing the cleaning and preprocessing, the models are trained using a dataset including nine years of historical load data from Canada combined with meteorological data (wind speed and temperature). The results revealed that using deep learning approaches of LSTM and NARX, the model was able to forecast load demand more correctly than RF and SVM, achieving a MAPE of 4–10% and an R-Squared of 0.93–0.96.

Mocanu et al. [187] used factored conditional restricted Boltzmann machine (FCRBM) and conditional restricted Boltzmann machine (CRBM) to forecast time series load consumption of three sub-meters and a household. They did short-, medium-, and long- term forecasting with time resolutions of 1 year, 1 week, 1 day, 1 hour, and 15 minutes. The FCRBM model surpassed all the other algorithms in terms of performance, and both CRBM and FCRBM proved to be more robust. Similarly, Samuel et al. [237] provides a CRBM-based methodology for medium-term load forecasting that combines hourly load demand and temperature data to forecast month ahead hourly load demand. A mutual data-based feature selection method is utilised for data preprocessing and a meta-heuristic optimisation algorithm is utilised to enhance the convergence and accuracy rate of CRBM. The results showed that the suggested model performed better than traditional methods in terms of convergence rate, accuracy, and execution time.

Yu et al. [303] used sparse coding for modelling and forecasting of volatile and stochastic household-level load for the next-week and next-day. They conducted a further case study on 5000 homes data in Chattanooga, TN, and the addition of the sparse coding features improved the forecasting accuracy by 10%. Estebsari and Rajabi [83] used a hybrid approach based on convolutional neural networks (CNN) and time series image encoding methods to address the problem of unpredictability of individual household load consumption. The performance of a real domestic customer's forecast using various encoder strategies was contrasted with other current prediction methods like ANN, SVM, and CNN. The image encoding method with best performance resulted in mean absolute percentage error (MAPE) of about 12%.

**Long-term Load Forecasting**

The utilisation of hourly and monthly data to develop a suitable long-term prediction model and increase forecasting accuracy is in high demand in the energy sector. Long-term load forecasting is particularly important for power system operations and grid expansion. In long-term forecasting, the load is predicted for one or more than one year. Wen et al. [291] proposed a Takagi-Sugeno (TS) fuzzy based RNN model for long-term forecasting. The model is based on two stages. In the first one, an original weather station selection approach is proposed and in the second stage an enhanced self-organising RBF-RNN is combined with a TS fuzzy model. The results confirmed that the proposed model performed better than its traditional version, GA-LSTM, FIR, SVR, and MLR.

According to some studies, ANN could produce erroneous load forecasts when utilised for long-term forecasting as the training data is somehow always limited. However, an improved ANN model was developed by Mohammed and Al-Bazi [188] comprising of an adaptive back propagation algorithm. The proposed model took into account the variations between future inputs and trained data and adjustment factors were also introduced. Monthly power consumption data from 2011 to 2020 was used and load shedding time was also considered. Results demonstrated that the proposed ANN model outperformed traditional and latest techniques such as RNN. The long-term forecasts were able to achieve MAPE of 0.045 and MSE of 1.195 and .650. Another novel dynamic feed-forward BP ANN algorithm for long term forecasting has been proposed in Masoumi et al. [180]. The model was tested using Canada's power network data and the results confirmed the effectiveness of the proposed approach.

An hourly load forecast for long-term has been proposed by Bhatia et al. [25]. The authors developed an ensemble model with first stage based on stacks of adaptive and gradient boost regressors and second stage based on Lasso LARS regressor to reduce the variance. Thirteen years of historical data from Germany's energy market has been used, out of which five years of data is used for testing the model. The proposed model surpassed all the traditional methods with MAPE of 1.59 and had lower computational costs when compared with ANN. An LS-SVM based approach has been used in Yasin et al. [301] to forecast long-term power demand. Weather data including humidity and temperature and wind speed were considered as inputs along with energy data. For enhancing the accuracy, a Grey Wolf Optimiser was used to minimise the MAPE-based objective function and find out optimal tuning parameters of LS-SVM. The proposed algorithm achieved MAPE of 0.13% and outperformed the other comparison algorithms.

Long term load forecasting is often limited to power demand data with annual or monthly resolution, which leads to low accuracy. However, now deep learning algorithms such as

LSTM have been able to forecast load for long-term using hourly load data as in Agrawal et al. [5]. This is particularly because LSTM can consider long-term dependencies in the input data. The authors proposed LSTM-RNN model and trained it using ISO New England data for 12 years. The forecasts were made for five years and the suggested model was able to achieve MAPE of 6.54 %. The model took only 30 minutes to compute, making it ideal for offline training to predict load demand over a five-year period.

### Point vs Probabilistic Load Forecasting

The short-, medium-, and long-term load forecasting techniques discussed above are referred to as point forecasting. In the previous decade, increased market competitiveness, old power infrastructure, and the demand for renewable energy deployment have made probabilistic load forecasting (PLF) play a crucial role in power system operation and planning. A PLF model is capable of extracting more details related to future uncertainties. A standard point forecast model typically consists of historical data input, load modelling, and the target response (the predictions). However, a probabilistic forecast can be developed in the following three ways:

1. Enhancing the PF outputs to PLF by developing point forecast ensembles or integrating modelled or simulated residuals
2. Using PLF models, for example, quantile regression
3. Developing various input conditions to send to a PF model

For example, a *quantile regression neural network* QRNN was proposed in (Gan et al. [101]) to produce next-year probabilistic load forecasting. Regular neural networks can only raise one output value at one point, but this is not suitable for probabilistic load forecasting. However, the proposed QRNN produced vectors comprising of quantiles by changing variables in the loss function. The results demonstrated that QRNN surpassed the reference models multiple linear regression (MLR), linear quantile regression (LQR), multi-layer perceptron (MLP), and maximum relative improvement (MRI)) in 7 zones. Similarly, Gaillard et al. [99] developed a probabilistic short- and medium-term load forecasting model based on a quantile generalised additive model (quantGAM). Different temperature scenarios were also developed to feed into the forecasting models. The results showed that quantGAM was computationally fast, easily implementable, and achieved best performance. A more detailed review on probabilistic load forecasting models can be found in works of Hong and Fan [126].

**Excess Generation Forecasting**

With the integration of renewable energy sources into smart grids, accurate energy output forecasting of PV grid-connected systems is particularly crucial for economic dispatch, grid stability, and optimal unit commitment. This is because generation from PV systems is highly volatile due to its reliance on weather and solar irradiance. Hossain et al. [130] developed a method to predict PV output power for 1 hour and 1 day ahead. The proposed ELM model was compared with ANN and SVR on the basis of MAPE, RMSE, and other performance metrics. The results confirmed the supremacy of the proposed model in terms of computational time and accuracy. Similarly, Malik et al. [178] proposed PV power generation forecasting model which considered the power degradation of old panels, which in turn increased the accuracy of the results. Another effective PV forecasting approach based on empirical mode decomposition and BPNN has been proposed by Yadav et al. [299]. The empirical mode decomposition algorithm first decomposes the power time series that is then utilised for training the BPNN.

There are many other PV power forecasting models in past research, however the author could not find a model which directly address the excess generation forecasting problem where behaviour is incorporated. Currently,forecasting models for the PV generation model and load are substituted for this problem, and excess generation itself is still considered to be a niche area of study.

### 2.2.3 Predictor Variables

Based on the research papers reviewed in this and the previous subsection 2.2.2, Table 2.2 summarises the possible predictor variables that can be fed to a machine learning forecasting model, depending upon application. The historical data that is used for load forecasting is transformed and organised into a ‘prediction matrix’ of m by n dimensions, where m would correspond to the number of time steps and n would correspond to number of predictor variables.

For short-term load forecasting, researchers are using smart meter load data with sequential parameters such as weekends, weekdays, calendar, and hour of day (Edwards et al. [77], Humeau et al. [133], Rodrigues et al. [232]), along with current values and forecasts of weather parameters such as humidity, wind speed, temperature, and irradiation to forecast domestic load (Gajowniczek and Ząbkowski [100]). Moreover, the number of electric appliances, daylight hours, energy consumed every minute, number of occupants, holidays, extreme weather events, important local activity, consumer price index, average of stock exchange, economic growth rate, and oil prices are some other predictor variables that are

Table 2.1 Best Machine Learning Models for short-, medium-, and long-term forecasting

| | **Best ML Models** | **ML Models used for Comparison** |
|---|---|---|
| Short-term~ Load Forecasting | Least Squares SVM (Edwards et al. [77]) | HME variants, FFNN, and FCM with FFNN models. |
| | Self-Recurrent Wavelet Neural Network (Chitsaz et al. [45]) | Simple WNN |
| | Iterative ResBlocks Deep Neural Networks (Hong et al. [129]) | ELM, SVM, and ARMA. |
| | Factored Conditional Restricted Boltzmann Machine (Mocanu et al. [187]) | ARIMA, CRBM, HWM, ANN, SVM, and RNN |
| Medium-term~ Load Forecasting | Group Sparse Coding Machine (Yu et al. [303]) | ARIMA and Holt-Winters smoothing |
| | Factored Conditional Restricted Boltzmann Machine (Mocanu et al. [187]) | ARIMA, CRBM, HWM, ANN, SVM, and RNN |
| | Quantile Generalised Additive Model (Gaillard et al. [99]) | |
| Long-term~ Load Forecasting | Quantile Regression Neural Network (Gan et al. [101]) | MLR, LQR, MLP, and MaxRI |
| | Factored Conditional~ Restricted Boltzmann~ Machine (Mocanu et al. [187]) | ARIMA, CRBM, HWM, ANN, SVM, and RNN |

frequently being used in literature for short term load forecasting (Chitsaz et al. [45], Mocanu et al. [187], Chaouch [41], Hsiao [131]).

For medium-term forecasting, previous week load, total previous day's load, moving average temperature, and lagged temperature variables are used in (Yu et al. [303]).

For long-term load prediction, median of monthly peaks, normalised monthly load peak, housing stock, employment rate, weekend, number of jobs, holidays, weekdays, dry bulb temperature, hour load, week load, demographic and economic variables, year load, month load, and weather are commonly being used as predictor variables (Hong et al. [128], Hyndman and Fan [135], Gan et al. [101]).

### 2.2.4 Forecast Evaluation

For assessing the performance of machine learning models, researchers often use performance metrics based on error calculation. In this thesis, six popular error metrics for evaluation of prediction have been identified (Edwards et al. [77] Chitsaz et al. [45] Lusis et al. [173]). The coefficient of variance (CV), given by 2.5, calculates how far the total prediction error fluctuates from the average value of actual load demand. A low CV rating represents that the model has a low a range of errors. Equation 2.6 gives mean bias error (MBE), which specifies how often the real load demand can be underestimated or overestimated by a specific model. A null MBE is favoured, as this indicates that the model will not support a specific pattern in its forecasting.

RMSE shows how the predicted data is clustered across the best fit line by calculating the standard deviation of the prediction errors and is defined by 2.7. Therefore, lower values of RMSE will indicate that the model has accurately forecasted the load. Normalised RMSE (NRMSE) as illustrated by equation 2.8 associates RMSE with the actual demand data. Mean absolute error (MAE) provides the average error magnitude in a prediction set and is defined by equation 2.9. Lower values of MAE will mean an accurate forecasting model. MAPE metric defines the error percentage in every prediction as can be seen in equation 2.10. Therefore, lower values of MAPE will mean that the model is more accurate.

$$\mathrm{CV} = \frac{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(y-p)^2}}{\bar{y}} \times 100 \tag{2.5}$$

$$\mathrm{MBE} = \frac{1/(n-1)\sum_{i=1}^{n}(y-p)}{\bar{y}} \times 100 \tag{2.6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum(y-p)^2} \tag{2.7}$$

Table 2.2 Predictor variables for short-, medium-, and long- term load forecasting (Chitsaz et al. [45], Mocanu et al. [187], Chaouch [41], Hsiao [131], Yu et al. [303], Hong et al. [128], Hyndman and Fan [135], Gan et al. [101])

| Predictor Variables | | |
|---|---|---|
| Short Term Load Forecasting | Medium Term Load Forecasting | Long Term Load Forecasting |
| Previous day load profile | Previous Week Load | Normalised monthly load peak |
| Previous week load profile | Total previous days load | Median of monthly peaks |
| Every minute load profile | Moving Average Temperature | Holidays |
| The surface of the property | Lagged Temperature | Weekdays |
| Number of electric appliances | | Weekends |
| Number of occupants | | Housing stock |
| Daily temperature | | Employment rate |
| Sunshine curves | | Number of jobs |
| Month | | Weather |
| Day of month | | Demographic variables |
| Day of week | | Economic variables |
| Holiday for work | | Hour load |
| Holiday for school | | Week load |
| Festival | | Month load |
| Important local activity | | Year load |
| Typhoon | | Dry bulb temperature |
| Relative humidity | | |
| Wind speed | | |
| Consumer price index | | |
| Economic growth rate | | |
| Average of stock exchange | | |
| Composite coincident Index | | |
| Hour of the day | | |
| Oil prices | | |
| Solar Irradiance | | |

$$NRMSE = \sqrt{\frac{1}{n} \cdot \sum_{t=1}^{n} \left(\frac{y-p}{y}\right)^2} \tag{2.8}$$

$$MAE = \frac{1}{n} \sum |(y-p)| \tag{2.9}$$

$$MAPE = \frac{1}{n} \sum \frac{|(y-p)|}{y} * 100\% \tag{2.10}$$

In all the above equations 2.5, 2.6, 2.7, 2.8, 2.9, and 2.10, n is the length of load data, p is the predicted load, y is the actual load, and $\bar{y}$ is the average load.

It is noteworthy that both NRMSE and MAPE are vulnerable if the actual load data is near or equal to zero, and thus produces a rather large error. MAPE is also sensitive to outliers and cannot adequately calculate each load forecast because of its time-shifting property. In Moreno et al. [193], a resistant MAPE (r-MAPE) was suggested to solve MAPE's behaviour to outlier values based on the Huber M-estimator estimate. R-MAPE can include outliers and does not permit them to control the error calculations. For dealing with the intermittent nature of individual power consumption, mean arctangent APE (MAAPE) has been developed in (Kim and Kim [154]). Equation 2.11 gives this variation of MAPE. It considers constrained impacts for outliers by regarding the ratio as an angle rather than a slope.

$$\text{MAAPE} = \frac{1}{n} \sum_{t=1}^{n} (\text{AAPE}_t) \quad fort = 1, \ldots, n \tag{2.11}$$

where $\text{AAPE}_t = \arctan\left(\left|\frac{y_t - p_t}{y_t}\right|\right)$

### 2.2.5 Problems in Load Forecasting

The problem the author has identified is that while there are established machine learning modelling frameworks for load forecasting, frameworks for direct modelling for customer load adaptation or excess generation were not available.

Regarding customer behavioural adaptation under different TOU tariffs, the reliance on historical data can have a number of drawbacks given that there is no in-built capability to model discontinuous user behaviour such as an adoption to a TOU tariff. Therefore we suggest that a dedicated data-driven model should be developed for this particular problem considering the discontinuity of user behavioural patterns due to an intervention of a TOU tariff. We name the problem as the "TOU load adaptation forecasting problem".

Similarly, regarding excess generation modelling, forecasting models for PV generation models and load are substituted for this problem. There are many research works such as Hossain et al. [130], Malik et al. [178], Yadav et al. [299] that have developed algorithms to predict the overall PV output power when connected with the grid but not the excess generation. Forecasting the excess generation from households is essential for utilities, as the cumulative installed capacity of residential PV systems is growing in many countries and this impact has become substantial for demand management. Thus we also suggest that a dedicated data-driven model should be developed for this particular problem. We name the problem as the "excess generation forecasting problem".

Furthermore, some of the recent machine learning works use complex models which might require a lot of time and computation power if dealing with millions of households. The cost of computing time is a widely known issue in the field of machine learning [258]. Specifically, a variety of recently successful neural network models inherently take time for their training due to their complex structure and numerous parameters. For instance, Hong et al. [129] proposed a ResBlock and DNN based method which increased the computational costs even with only 196 data points for testing and 200 epochs for training, which took 101.7 seconds to train the proposed model. In addition, FCRBM used in Mocanu et al. [187] processed about 2,075,259 instances of load consumption data in the form of images and stated that the computational complexity of the suggested algorithm would increase when generating the proposed image encoded data realistically. Similarly, the authors in Hsiao [131] used 400 days of data with 98 readings per day, and there is no guarantee that the same Ward's linkage-based approach would perform well when the dataset gets quite large.

Considering the millions of smart meters installed which continuously generate billions of data points everyday across the world and the importance of continuous re-training the modelling parameters, computational time should also be highly considered in the modelling. Thus, this thesis suggests a way to improve the accuracy of classic machine learning models by introducing new features that capture the characteristics of load profiles efficiently. More specifically, statistical moments are introduced in Chapter 3 and 4 as an effective feature for different tasks related to load prediction error while keeping the computational cost low.

## 2.3 Load Management

Smart meter data is also contributing to the management of DR programs by assisting the researchers in finding the right customers for DR program marketing and solving the problems regarding their implementation. Despite the large potential of TOU tariffs for helping to achieve carbon neutrality, we cannot force consumers to switch to a TOU tariff without their consent in the real world. Particularly in the competitive deregulated energy market such as the UK and Japan, energy companies are reluctant to sell a TOU tariff, which has a higher cost of explanation to the customer and a risk of losing customers to a competitor offering a simple single-rate tariff. Therefore it is important to find the right customers who would likely to be well-suited for a DR program. This sections covers relevant techniques to identify the right customers for a DR program: the customer characterisation (3-a) and demand response program marketing (3-b) under the categorisation in Wang et al. [281]

## 2.3.1 Customer Characterisation

Customer Characterisation is the grouping of customers for developing dedicated tariff plans according to their load profiles or patterns of energy consumption. The customer classes are created automatically using clustering methods, which can use both direct and indirect methods. The load profile for each customer class is then used to depict it. Direct clustering refers to clustering which can be immediately applied to smart meter data, whereas indirect clustering is when the smart meter data requires pre-processing by methods such as dimension reduction methods.

**Customer Characterisation based on Direct Clustering**

Chicco [44] examined direct clustering methods such as k-means (KM), follow the leader (FDL), fuzzy k-means (FKM), and the hierarchical clustering (HC) variants for electrical load pattern classification. When the utility requires a load pattern partitioning directly from the clustering algorithm with the number of groups equal to the number of user groups that they aim to create, the use of hierarchical clustering variants could not be sufficient, and an approach such as KM would be more suitable. In comparison, for outlier detection, hierarchical clustering variants might be used efficiently, whereas KM and FKM would be obviously unsuccessful. According to Wang et al. [283], another direct clustering method - self-organizing map (SOM) - was compared with KM, FDL, HC, and FKM, and the findings confirmed that hierarchical clustering and follow-the-leader methods surpassed the other methods, and can deal with the unusual isolated load.

However, direct clustering methods often encounter a few fundamental problems. The first problem is the smart meter data resolution. In (Granell et al. [113]), three common clustering techniques - the Dirichlet process mixture model (DPMMs), hierarchical algorithms, and KM - were used to examine how the smart meter data influences clustering results with different frequencies ranging from 1 minute to 2 hours. They discovered that the smart meter data is effective for most purposes if it has a temporal resolution of at least 30 minutes. The KM algorithm appeared to be quicker and reliable in a 4-60 minute range of time resolutions.

The second concern of direct clustering methods is that the data from the smart meter are mainly time series data. Unlike conventional static data clustering methods, Benítez et al.

[24] suggested a modified KM algorithm for the dynamic clustering of the time-dependent residential electricity consumption data. The dynamic clustering quickly identified and grouped the main patterns of consumer data. In (Al-Jarrah et al. [9]), a two-stage clustering model was suggested for resolving the problem of the computational complexity of the tremendous volume of data in power consumption load profiles. During the first phase, KM algorithm was used to produce local representative load profiles (RLP), while in the second step, a central processor developed a global RLP by again clustering the cluster centres obtained in the first stage. The multi-layered model was successfully able to dramatically reduce the computation and brought down the expenses of the load profiling process.

#### Customer Characterisation based on Indirect Clustering

Many works in the research literature are also emphasising on indirect clustering, using different methods for feature extraction and smart meter data dimension reduction before performing clustering. In Koivisto et al. [159], the authors used principal component analysis (PCA) to reduce the dimensions of huge yearly load profiles data of 18098 customers. After that, they used KM clustering for classifying the customers and multiple regression analysis to explore the explanatory parameters for load modelling. The components obtained from PCA can disclose the power consumer pattern of various types of connection points. Likewise, Chelmis et al. [42] used PCA to identify the time trends of individual consumers and the spatial pattern of many consumers. After that, a new K-medoids algorithm, depending upon Voronoi decomposition and Hausdorff distance, was suggested for outlier detection and clustering the load profiles. The method proved to be efficient on a large number of data points.

Ward et al. [287] proposed an original functional data analysis (FDA) technique based on functional PCA for classifying daily power consumption of lighting and plug loads. They demonstrated how the FDA model can produce stochastic input data for simulating energy consumption of a building. Hierarchical clustering was utilised to investigate how the building loads are linked to 'activity' as described in a database. It was found out that plug load clusters are more closely associated with the activities, whereas, the lighting loads are primarily linked with the amount of data variability.

In order to find valuable typical load profiles, knowledge of the global and local features of the smart meter data is vital. In (Morán et al. [192]), the authors proposed deep convolutional autoencoder for feature extraction of the load profiles. They further identified their effect on the main supply point to assist in developing a global load supply profile. Three new kinds of features were introduced in (Al-Otaibi et al. [10]) for clustering daily load profiles by using conditional filters on features based on meter resolution combined with calibration and normalisation, shape signatures, and profile errors. The suggested feature extraction technique had small computational complexity, and the extracted features were understandable and informative in describing patterns of power usage. In (Piao et al. [218]), 10 sub-space clustering and forecasted clustering techniques have been implemented to recognise consumer contact type in order to produce global and local shape variations. The clustering process has proved to be more resilient to noise by relying on the load profile subspace.

In customer characterisation methods, the irregularity, uncertainty, and high stochasticity of smart meter data have also been addressed. Four major time frames describing various peak demand patterns overlapping with common day intervals - breakfast, overnight, evening time, and daytime - were defined in (Haben et al. [117]). After that, ten different behaviour classes were classified, using clustering based on a finite mixture-model, to represent customers based on their volatility and demand. In (Sun et al. [260]), a mixture model was also utilised for the clustering of domestic power consumption profiles by the C-vine copula method. The method was used to model the high-dimensional non-linear associations between the power consumption of various time frames. This technique also performed efficiently in large sets of data.

### 2.3.2 Demand Response Programs Marketing

In demand response marketing, consumers are evaluated based on factors such as their potential for participating in a demand response program, total or peak load, bill savings, and reliability of participation. However, smart meter data with a resolution of 15-30 minutes does not provide deep insights into other forms of potentially valuable information - such as appliance type and operating status. Furthermore, consumer understanding and receptivity towards demand response is also difficult to model. Therefore, there are a number of difficulties directly evaluating the consumer potential for demand response. Popular works that are evaluating DR potential indirectly are examining variability and appliances, and these are detailed in the following subsections.

#### Variability

Variability is a crucial metric for determining the demand response potential. Albert and Rajagopal [11] have proposed a hidden Markov model (HMM) to estimate the user's state sequence using residential time series data. Spectral clustering was used to distinguish power consumption data by duration, variability, and magnitude. Occupancy states data, patterns of inter-temporary consumption, and variability information could allow marketers or aggregators to reach appropriate customers at various time frames.

Hierarchical clustering and adaptive KM algorithm based encoding system was used for household power segmentation in (Kwac et al. [162]). A residential daily load profile of one year consisting of over 66 million data points was pre-processed, and segmentation was performed within a specific error threshold. The authors stated entropy performance metric (given by equation 2.12) to track the load variability of each user and categorise his load profile. In equation 2.12, $p_n(C_i)$ is the relative frequency of every encoding cluster centre $C_i$ in the daily load profile of every household $n$.

$$S_n = -\sum_{i=1}^{K} p(C_i) \log p(C_i) \tag{2.12}$$

The entropy will be lowest if the user only has a one cluster centre and highest if the user's load profile have cluster centres that are equally likely to be present in the database. In other words, the average entropy would be lower on weekdays as users follow a regular routine on weekdays when compared with weekends. If any user's entropy quantile was more than 75%, it was considered as an irregular or variable user, and for users with quantile less than 25%, they were labelled as stable users. The authors concluded that lower entropy consumer load profiles with less variability were easy to predict and more stable, and therefore had a higher potential for demand response. Similarly, users with high entropy will not be good candidates for DR events as their energy activities and usage will be more variable, but they will be good candidates for energy efficient programs like rebates.

However, Wang et al. [282] contradicts this with the finding that high entropy users may not have a good potential for demand response. They claimed that the users with high usage, high entropy level, and thus high variability are fit for price-based DR such as TOU pricing, as they have adaptability for altering their usage. Lower entropy users may also be targeted for other types of DR programmes as they are less variable and easier to predict. Wang et al. [282] claimed that users with minimum entropy and high usage level are good candidates for incentive-based DR such as direct load control (DLC). They are more likely to use the same load and their control is predictable. Albert and Rajagopal [11] conducts a similar analysis as Wang et al. [282] in a comprehensive classification of energy consumption of consumers by differentiating into regular and random consumption patterns. The users with regular or predictable load should be considered essentially different from the random ones for efficiency and demand response programs for balancing load in the smart grid. The users with irregular or random load can be suitable for participating in peak-pricing DR, which in turn may also stimulate more regular usage. On the other hand, predictable consumers offering less versatility in their usage, are potential candidates for energy efficiency programs offering rebates for reducing the power consumption of electrical appliances.

### Appliances

Another way of finding suitable customers for demand response is to calculate the potential reduction in power consumption by analysing the energy demand of electric appliances and the consumer's behaviour towards controlling the active demand of appliances. In (Labeeuw et al. [164]), a mixture model was developed to cluster similar residential load profiles. Clusters were made to estimate the active demand reduction potential of "wet" appliances including dishwashers, tumble dryers, and washing machines. The study found that both the power consumption of the residential wet appliances and response towards DR have a high potential for shifting demand. Similarly, Jindal et al. [146] proposed a two-stage methodology for the management of DR and flattening the residential load curve. The authors first used an SVM classifier to identify consumers and appliances with surplus power consumption, and then that surplus load is shed by using a rule base on a load balancing algorithm. The authors claimed that the user with surplus load would be the best choice for demand response and SVM achieved a recognition accuracy of 88.5%.

Given the high DR potential of devices such as heating, ventilation and air-conditioning (HVAC) systems, their power consumption sensitivity to ambient air temperature is an efficient assessment measure. Linear regression and unsupervised classification were used in (Dyson et al. [73]) to estimate this sensitivity of a residential air conditioning system. Also, the maximum likelihood method was applied to find out the best change-point for every model. This allowed the authors to approximate DR potential at various hours of the day. A hidden Markov model (HMM) and thermal regimes-based temperature response model was developed in (Albert and Rajagopal [12]). The authors used the temperature and hourly load data to divide the individual load data into a temperature sensitive and non-sensitive part. To choose the best DR user, a basic selection problem to optimise an averted load consumption was utilised, and the developed model can get very high savings when compared with a random method. Figure 2.5 summarises some of the best candidates for demand response programs for residential, commercial, and industrial customers in terms of availability of electric appliances.

Electric appliances are usually defined as thermostatically controlled appliances (TCL), non-thermostatically controlled appliances (non-TCL), and devices with batteries. Thermostatically controlled appliances include refrigerators, water heaters, HVACs, and freezers. Non-thermostatically controlled appliances refer to a further category of non-urgent and urgent loads. Urgent loads are those loads that must instantly turn on or off once a command is given by the consumer - for example, cooking appliances, lights, fans, entertainment appliances. Non-urgent loads can be operated after certain time periods, such as laundry machines, dishwashers, and dryers. Loads or devices with batteries mostly include electric

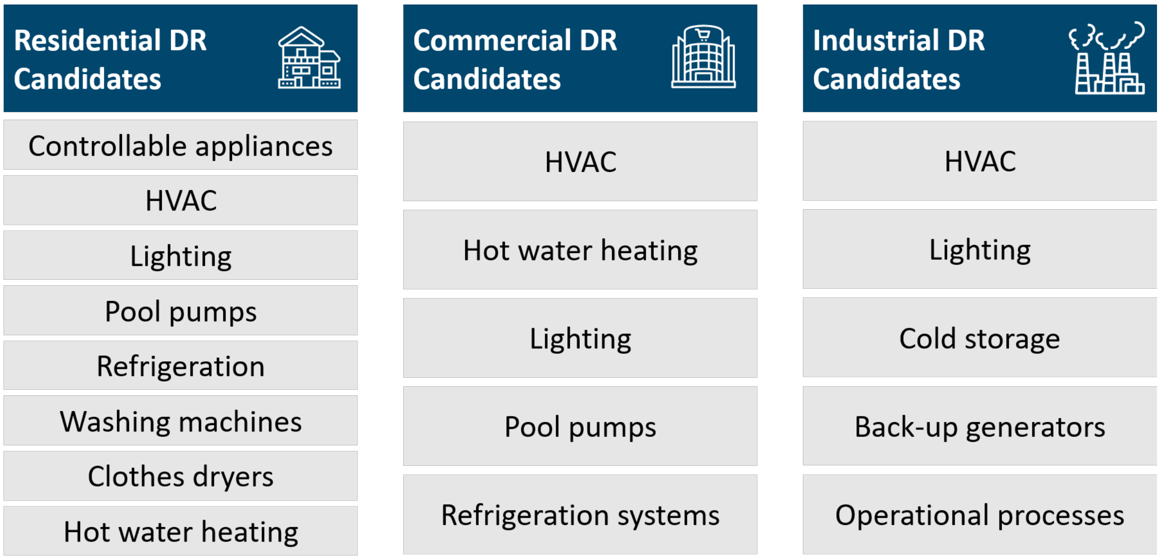



Fig. 2.5 Best Consumers for Demand Response Programs (based on Ponds et al. [222])

vehicles. Tulabing et al. [272] have checked the DR potential for flexible loads at substation level. Figure 2.6 shows the concept that they adopted to calculate aggregated DR potential from households. Their developed algorithm allowed the DR controller to aggregate the TCL, non-TCL, and battery-based loads in households for DR programs. The users could send requests for turning on the load and then the DR decides whether to turn it on according to the available power.

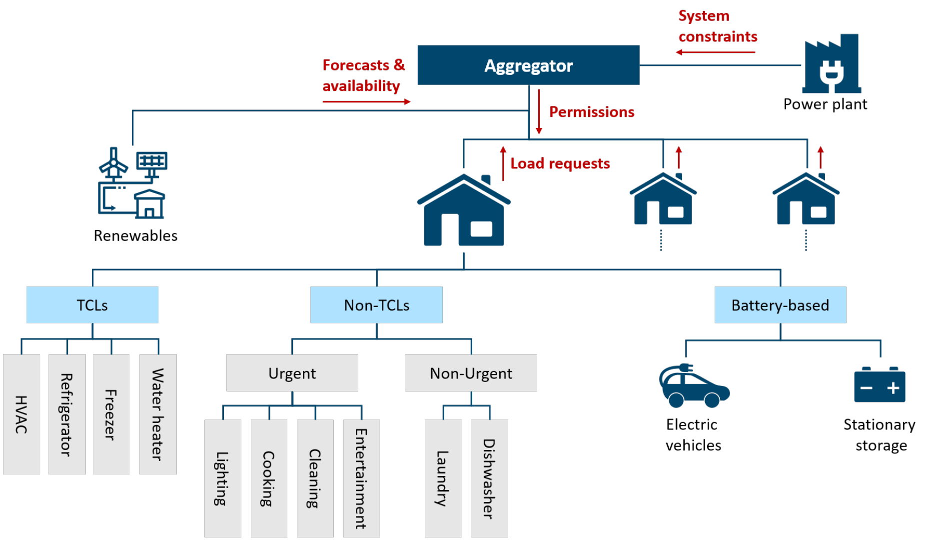



Fig. 2.6 DR aggregator controlling flexible loads at sub-station level (based on Tulabing et al. [272])

### 2.3.3 Problems in Load Management

The problem the author has identified is that the suitability of an individual customer toward a TOU tariff is still not being well addressed. We found that some papers (Kwac et al. [162], Albert and Rajagopal [11], Wang et al. [282]) reached contradictory conclusions to identity the suitable customer for a TOU tariff. Kwac et al. [162] stated that higher entropy users may not be good candidates for DR as their routine is variable and is not easy to predict. However, Wang et al. [282], Albert and Rajagopal [11] stated that this variability in their routine makes them a good candidate for price-based DR since their variability would allow them to adapt their power consumption according to the electricity prices. But these works are theoretically examining the historical load and do not examine an actual empirical dataset (perhaps due to the limitations of available public datasets). Thus we suggest that more data-driven works are needed to identify the right customer using the actual datasets.

Furthermore, in practical use, user engagement towards a TOU tariff needs to be considered for identifying the right customer (Cousins et al. [52]). Any introduced tariff plan may fail if it does not take account of the customer's point of view (Eskom [82]) . Although it is difficult to quantify the customer willingness, a means of enhancing the engagement can be a meaningful variable for this modelling. An emerging concept of "gamification" has the potential to improve customer adaptation in a TOU trial with a marginal financial cost. 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 [243]). Therefore, we also suggest to incorporate this "gamification" in the further research of a forecasting model to identify suitable customers toward a TOU tariff.

We name the problem discussed in this sub chapter as the "TOU winner detection problem".

## 2.4 Public Load Datasets

These modelling studies require a dataset (such as historical electricity consumption and some households variables), and scarcity of these public datasets can be a major barrier to overcome. Therefore this section investigates any available public dataset this paper can use for the data-driven modellings.

Electric utilities are frequently unwilling to disclose their smart meter data publicly because of many problems such as security and privacy. There are dozens of historical load anonymised or semi-anonymised databases that have been accessible to the public throughout the last several years. However, when it comes to a dataset of a demand response trial, the number of the datasets becomes very limited.

### 2.4.1 Load Datasets of Demand Response Programs

The following part summarises six major public load datasets of demand response programs (also summarised in Table 2.3).

- Customer Behavior Trials. Ireland's regulator of the electricity and natural gas industries, Commission for Energy Regulation (CER), initiated one of the largest customer behaviour trails (CBTs) using smart meters. The trials were conducted to check the potential of smart meter data together with various DSM stimuli and TOU tariffs for achieving measurable changes in total power usage and peak demand reductions of consumers. Furthermore, the residential CBT also recognised a "tipping point", where energy price would considerably change the power consumption of the user. The CBR assessed if smart meter data would help change the power consumption pattern through a range of home sizes, lifestyles, and demographics (Gungor et al. [115]). The data was collected from July 2009 to December 2010 of more than 5000 Irish households and industries. After data pre-processing, the dataset recorded measurements of 4225 meters for more than 536 days. Out of these meters, 3296 smart meters were used as a test group. The findings of the trials showed users with overall 2.5 % total power demand reduction and 8.8 % average reduction in peak demand.

- Low Carbon London. Like CBTs, a study involving more than 5000 homes was conducted in London as a section of the low carbon London initiative (Schofield et al. [240]). Time of Use (TOU) data, smart meter data, and survey data were gathered to study the effect of a variety of low carbon technologies on the power distribution system of London. The project was supported by Ofgem and collected readings from 2011 to 2014. In 2013, dynamic TOU tariff was offered to 1122 homes out of the total 5567 households.

- PecanStreet. Pecan Street TOU and customer behaviour trial was conducted in Austin, TX to develop this database (Pecan Street Inc. [215]). Peacan Street also recruited homes from the Mueller neighbourhood. The dataset includes minute-level energy consumption data of 280 homes from 2013 to 2014 at both appliance- and whole home-level. Each home out of the 256 dwellings in the Mueller area was randomly allocated to the five groups. The first group (control group) included 57 households that did not receive any new tariff plan. In the second "passive" group, 44 homes did not receive a new tariff plan but could visit an online portal that monitored their usage of electricity at the appliance level. In the third "active information" group, CPP was offered to 46 homes and they were informed 24 hours earlier than the issuance of the event using a text message. For example, the text message would include: “A Pecan Street Project critical peak event is taking place tomorrow from 4 PM to 7 PM.” In the fourth group (active information+recommendation), the same text message was sent to the 47 homes, which asked them to perform one of the following actions: "Pre-cool your home,” “Reduce your air conditioning usage,” or “Do not use your clothes dryer.” The last pricing group issued CPP to 62 homes only from June to September (summer season). Again, text messages were sent 24 hours before the issuance of CPP. In this group, nighttime pricing was also offered from March to May and in November and December. The lowest offered rate was 2 cents/kWh.

- Ausgrid Resident. The Ausgrid distribution system recorded half-hourly rooftop PV production data and smart meter data from 300 domestic users for three years in an Australian distribution system (Ratnam et al. [229]). Three smart meters were installed to record PV generation for FIT tariffs, domestic power usage according to an inclining block rate or TOU, and controllable load related to electrically heated water systems. The gross metering mode measurements of domestic power usage were recorded according to the user’s preference of registering under TOU tariffs or inclining block rates. The financial rewards associated with off-peak 1 or off-peak 2 were offered to 137 homes in which the electrical company controlled the watering heating systems of the users. In the off-peak 1 tariff plan, the users allowed the electrical company to turn off their water heating system for 18 hours each day. The off-peak 2 plan was more expensive as the utility was only allowed to turn off the water heating systems for only 8 hours each day.

- ISO New England. The demand data at system-level and subsequent temperature data of nine zones are released on monthly basis by ISO New England. The readings include real-time demand, day-ahead demand, system load, locational marginal pricing (LMP), and regulation clearing price information. Further specifics are available at (ISO New England [141]).

- Smart Grid Smart City (SGSC) is another publicly available DSM dataset. SGSC customer trial was started by Australian Government in 2010 and lasted for 4 years. It has collected data from smart meters installed in 10,000 individual homes in New South Wales and can be found at (Australian Government [20]). It contains user TOU (half hour increments) and population information, as well as comprehensive statistics on the usage of appliances, retail offers, environment, distributor product offers, and other similar variables. The offered pricing plans were seasonal TOU, dynamic peak pricing plan, rebates for interruptible load such as AC, and top-up tariff incentive (Norris et al. [199]). During dynamic peak pricing, the offered price was $3.00/kWh that was six to seven times more than normal TOU peak prices. Users were attracted by offering either off-peak prices or shoulder prices outside of the peak time. The seasonal TOU aimed at reducing summer and winter peak demand by offering peak prices more than normal TOU rates. The researchers checked whether users would shift their energy usage to other times and reduce the load during winter and summer peaks. In summers and winters, users were charged according to peak, off-peak, and shoulder TOU rates. However, in autumn and spring, only off-peak and shoulder rates were offered.

### 2.4.2 Problems in Public Load Datasets

The identified problem is that these public datasets of demand response trials are still limited, and repetitively used for research works. This is mainly due to the low public acceptability of DR programs and the expenses involved for conducting trials. For example, customer behaviour trials Irish public dataset has been used in research works of Quilumba et al. [225], Wen et al. [290], Li et al. [167], Wang et al. [284]; Low Carbon London DR data has been used in Wang et al. [284], Sun et al. [259], Dong et al. [69]; PecanStreet TOU data was utilised in Brown et al. [33], Perez et al. [217], Donaldson and Jayaweera [68]; Ausgrid resident data from the Australian distribution system has been used by Sunny et al. [261], Karandikar et al. [150], Razavi et al. [230]; and ISO New England data has also been used by many researchers (Sahay and Tripathi [236], Parsons and De Roo [213]).

Another problem is that the most recent currently available dataset above is relatively old (up to 2015), especially when considering that customer electricity consumption behaviour can change from year to year. Therefore, a more recent dataset will be required in this field.

We name the problem discussed in this sub chapter as the "TOU public dataset problem".

## 2.5 Identified Research Gaps

The author has critically assessed the past works in the relevant fields, and identified four major research gaps which need to be filled in order to expand commercial applications of TOU tariffs. The four research gaps addressed identified in this chapter will be addressed in the following chapters: the "TOU load adaptation forecasting problem", the "TOU winner

Table 2.3 Public Load Datasets (Wang et al. [281])

| Name | Brief Description | Number | Frequency | Duration | Country |
|---|---|---|---|---|---|
| Customer Behavior Trials [115] | Smart meter read data; Pre- and post-trial survey data; | 6445 | Every 30 min | 2009/9 to 2011/1 | Ireland |
| Low Carbon London [240] | Smart meter read data; Electricity price data; Appliance and attitude survey data; | 5567 | Every 30 min | 2013/1 to 2013/12 | UK |
| PecanStreet [215] | Residential electricity consumption data; Electric vehicle charging data; | 280 | Every 1 min | 2005/5 to 2017/5 | US |
| Ausgrid Residents [229] | ~PV~output data; Controlled load consumption data; General consumption~data; | 300 | Every 30 min | 2010/7 to 2013/6 | Australia |
| ISO New England [141] | System load data; Temperature data; Locational marginal pricing data; | 9 | Hourly | 2003/1 to now | UK |
| Smart Grid Smart City [20] | Smart meter read data; Electricity price data; SM TOU and geographical data; | 10000 | Every 30 min | 2010 to 2014 | Australia |

detection problem", the "TOU public dataset problem", and the "excess generation forecasting problem". By bridging these gaps, this thesis aims to establish a foundation for helping utility companies conduct practical analysis of smart meter data, and encouraging the larger scale implementation of a TOU tariff. The following paragraphs briefly summarise the identified four research gaps, and further detailed literature reviews will be conducted in each chapter.

Firstly, a practical framework to *forecast* users' load adaptation under different time-of-use tariffs has not been fully developed despite the existence of a large body of research on load forecasting. This load forecasting capability is important for utilities to design a TOU tariff and estimate subsequent impacts in their load management. These modelling frameworks generally follow one of the three distinct approaches: econometric models with an emphasis on estimating price-elasticity, bottom-up disaggregation of household consumption according to electrical appliances and their time of use, and top-down statistical models. The emergence of historical smart meter data makes the top-down statistical approach popular in industrial use. However, the reliance on historical data can have a number of drawbacks given that there is no in-built capability to model discontinuous user behaviour such as an adoption to a TOU tariff. Therefore applying a top-down approach for a problem of forecasting consumer response to TOU tariffs is a challenging issue. This issue is referred as "TOU load forecasting problem".

Secondly, although time-of-use tariffs have the potential to be mutually beneficial - realising a cost reduction for both energy companies and customers if the customer responds to the price signalling - at the individual level such tariffs are likely to create both positive and negative financial outcomes because of customer characteristics and the potential capacity for peak shifting. Identifying the potential reducers or non-reducers before applying a time-of-use tariff can optimise the programme's design and marketing strategy, which can maximise the outcome of a TOU programme. Factoring user engagement into a TOU program in a data-driven model is also challenging issue. This issue is referred as "TOU winner detection problem".

Thirdly, 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. Only a dozen sources of open data are available as the power companies are reluctant to release their smart meter data owing to security and privacy concerns. Learning a lesson from other fields where publicly available datasets have spurred previous applications in machine learning and data mining, a wider range of public data sets related to a TOU tariff intervention would enable further examination in this field. This issue is referred as "TOU public dataset problem"

Finally, if rooftop PV panels are installed at a household, predicting net demand after accounting for energy consumption behaviour becomes complicated. During PV system operation (day time), electricity generated by the PV panels does not often match electricity needed by households. When electricity generation exceeds household demand, excess electricity generation can be exported to the electricity grid. Forecasting the excess generation from households is essential for utilities, as the cumulative installed capacity of residential PV systems is growing in many countries and this impact has become substantial for demand management. Although this is not strictly a time-of-use tariff itself, these programmes effectively function like a time-of-use tariff, encouraging demand adaptation to maximise the financial incentives given by a subsidy. Thus, we apply the similar methodology we have developed for the TOU adaptation load forecasting models into this problem. This issue is refereed as "excess generation forecasting problem"

The following three chapters will address these four problems. Chapter 3 address the first problem, Chapter 4 does the second and third problems, and Chapter 5 does for the last problem. The author believes that proposing practical solutions toward these four problems will enable the commercial expansion of applications of TOU tariffs at the national level.

# Chapter 3

# Intra-Day Load Profiles under Time-of-Use Tariffs

## Highlights

- A model to forecast user adaptation under different Time-of-use tariffs.
- Lifestyle constraints are considered as key inputs in the form of statistical moments.
- The model requires only a half-hourly sampled historical smart meter data.
- Random Forest outperforms Neural Network and Liner Regression models.
- MAPE of the best model reports 2.05% for the weekday.

## Collaborators

- Yeonsook Heo[1] contributed to the discussion on the modelling of the proposed approach.

The first analysis chapter addresses the "TOU load adaptation forecasting problem", defined in the Chapter 2. This chapter briefly overviews the current circumstances of a TOU tariffs implementations, and more detailed examination in existing approach toward the load forecasting problem in a "TOU tariff before presenting the modelling works.

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## 3.1 Introduction

Residential energy sectors worldwide are facing the emerging development of smart meters combined with better techniques for streaming and processing large volumes of metering data into useful information. The ongoing roll-out of smart meters provides a clearer impetus for increasing policy support of demand-side management (DSM) solutions than ever before (Torriti et al. [269]). Time-of-use (TOU) tariffs, also known as time-dependent pricing, are a DSM solution wherein the price of electricity varies depending upon the time of the day and the day of the week. The tariff structure is designed to yield potential price savings for the end-user, and targets peak electricity load shifting to constrain the electricity load on a given sub-station. Studies have shown that TOU tariffs can be particularly effective in the residential sector, as they offer a more certain financial incentive to customers than other more complex price-based DSM programs such as real time pricing (Darby and Pisica [55]).

Alongside smart meter installation, by 2020 TOU tariffs will become available in most of the EU, United States, Japan, and Australia (ABI Research [2]). The success of TOU tariffs as a DSM solution depends upon consumers changing the timing of their energy demand based on a given tariff structure. Recently, large-scale longitudinal studies have been conducted to evaluate the behavioural change of residential customers pre- and post-intervention of a TOU tariff. The Customer-Led Network Revolution (CLNR) project in UK (Wardle et al. [288]) confirmed load shifting from peak to off-peak periods throughout a two-year trial with 576 households. Torriti [267] monitored 1446 households in Northern Italy and showed that while TOU tariffs result in a significant level of load shifting in the morning, the evening peaks do not change and overall consumption is in fact increased by 13.69%. Faruqui and Sergici [88] examined 15 pilot projects that showed TOU rates induce a drop in peak demand that ranges between 3% and 6%. Wang and Li [286] reported that potential peak reduction in the residential sector is much smaller than that of the commercial and industrial sector based on Federal Energy Regulatory Commission [91] survey. On the other hand, Faruqui et al. [89] concluded that residential customers are more price responsive than small business customers. They also examined estimates of the price elasticity of demand across 42 different TOU studies, and found a positive relationship between peak to off-peak price ratio and peak reduction. Gils [107] confirmed that household consumers hold a large potential load reduction in most European countries.

To date a large scale implementation of TOU tariffs has not taken place. In recent years, researchers have developed modelling frameworks which can allow utility companies to exploit smart meter data in order to predict potential load shifts when designing TOU tariff structures. These modelling frameworks generally follow one of the three distinct approaches: econometric models with an emphasis on estimating price-elasticity, bottom-up dis-aggregation of household consumption according to electrical appliances and their time of use, and top-down statistical models.

A classical approach estimates price-elasticities of demand distinguishing between the elasticity of demand due to price changes of the good itself (own-price elasticity) and of other goods (cross-price elasticity). The own-price elasticity provides an estimate of the percentage change in usage during a particular period (i.e. day or billing period) that results from a 1% change in price during that period. The cross-price elasticity provides estimates of the elasticity of substitution between peak, mid-peak, and off-peak periods. For example, Kirschen et al. [156] modelled consumer behaviour using a matrix of own-price and cross-price elasticities and showed the effect of market structure on the elasticity of the demand for electricity. Goel et al. [108] modelled customer response using the matrix of own/cross-elasticities, based on the assumption of constant elasticities. Venkatesan et al. [276] emphasised the importance of distinguishing between different consumer types considering different scenarios and levels of consumer rationality. Recently, Katz et al. [151] employed a similar approach to evaluate load-shift incentives for household demand response, comparing the effects of hourly pricing and a simple rebate scheme. An advantage of these approaches follows from the assumption that price-elasticities of demand are scale free, and under certain assumptions, are applicable out of sample. However, most of these studies have been conducted prior to the roll-out of smart meters. The integration of this classical approach with newly available energy big data is a new challenge in this field.

An alternative approach considers the potential for load shifting at the level of individual appliances, utilising information on the dis-aggregation of total household consumption according to electrical appliances (or activities). The advantage of this approach is the ability to identify the primary cause of load variation by associating load-shifting with appliances. For example, Armstrong et al. [17] computed consumption profiles for different types of activities based on publicly available data on energy use. Gottwalt et al. [112] applied this to evaluate the capability of residential load shifting when smart appliance and TOU tariffs are applied. Shao et al. [245] proposed a physics-based residential load model at the appliance level based on controllable load such as space cooling/heating, water heater, clothes dryer, and electric vehicles for demand response modelling. McKenna et al. [183] also constructed a bottom-up demand response model, combining multiple models such as hot water demand model and thermal appliances. Xu et al. [298] explicitly acknowledged variability across consumer response by applying a shifting boundary to limit the maximum load-shift in certain groups of customers.

A disadvantage of this approach is the requirement of ex-ante identification of demographic or appliance variables or the installation of additional sensors to record activities that influence consumption. This is difficult to access without dedicated and costly studies and must be continuously updated as household appliances and activities change. This point is also emphasised by Armel et al. [16] recommending a 1-minute to 1-second data frequency to infer the usage of key appliances.

The last framework is a top-down approach based on the use of statistical models using consumption data. A top-down approach usually treats the load at an aggregated level and does not distinguish energy consumption due to individual consumers or any appliances (see Swan and Ugursal [263]). The strength of a number of top-down models is the emphasis on historical energy consumption, which is indicative of the expected pace of change with regards to energy consumption. This approach is used widely by utility companies to forecast future energy demand. 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 used for medium-term electric load forecasting (see Hahn et al. [118] and Hernandez et al. [122]). However, the reliance on historical data can have a number of drawbacks given that there is no in-built capability to model discontinuous user behaviour such as weather changes, introduction of new appliances, and an adoption to a TOU tariff. Therefore applying a top-down approach for a problem of forecasting consumer response to TOU tariffs is a challenging issue.

This chapter presents a new top-down framework for predicting load profiles following the introduction of a TOU tariff, using demographics and historical electricity usage in the pre-intervention period. The influence of a TOU tariff introduction is usually evaluated with a time-horizon of one month to one year, comparing electricity consumption during pre/post introduction. In terms of the time-horizon, this work falls into the category of medium-term load forecasting. This chapter emphasises that this forecasting problem differs from standard medium-term forecasting models given the need to account for consumer behaviour adaptation to a TOU tariff.

The accuracy of a prediction model plays a vital role in making important decisions on the operation and planning of a power utility system (Hippert et al. [123]). The measure most frequently used to assess the accuracy of a medium-term load forecasting model is Mean Absolute Percentage Error (MAPE) (Hahn et al. [118]). However, current studies in TOU prediction do not report the accuracy of their models in a standard form. Without such a standardised measure of accuracy, it is difficult to compare the performance of the competing TOU models.

Although there exists a large body of research on demand response in electricity pricing, a practical framework to forecast user adaptation under different TOU tariffs has not fully developed. The novelty of this work is to provide the first data driven modelling of residential customer demand response following the adoption of a TOU tariff. In particular, this study evaluates the importance of lifestyle constraints which are constructed using statistical moments based on historical usage. The question as to the relative importance of demographic information and historical load profiles in the context of forecasting the impact of TOU on demand response, is of considerable interest to both companies and policymakers.

The key contributions of this chapter are summarised below.

1. The first top-down statistical model designed to *forecast* residential customer demand response following the adoption of a TOU tariff, and evaluate its predictive performance accuracy using MAPE.

2. The first model to explicitly include lifestyle constraints influencing user adaptation to a TOU tariff.

The remainder of this chapter is organised as follows. Section 3.2 introduces the dataset used to develop and test the modelling framework. In Section 3.3, the dataset and a list of relevant features for model development are described. Relevant statistical techniques and the accuracy of measurements are discussed in the Section 3.4. In Section 3.5, a number of summary measures demonstrate the predictive accuracy, comparing with other studies. The final Section concludes the work with limitations and future works. This work focuses exclusively upon *active* demand response due to behaviour adaptation. As such it is assumed that no automated energy storage is present in the sample households.

## 3.2 Data

The dataset used in this study is taken from the Electricity Smart Metering Customer Behaviour Trial carried out by the Irish Commission for Energy Regulation [49] (CER) . This is a public dataset (reviewed in the previous chapter) and can be accessed using Irish Social Science Data Archive ISSDA [142]. It consists of half hourly observations for a total of 4232 households, with a benchmark period of approximately 6 months and a trial period of one year.

This dataset is repetitively used in some existing works such as Quilumba et al. [225], Wen et al. [290], Li et al. [167], Wang et al. [284]. For instance, Quilumba et al. [225] used residential half-hourly power consumption data of 17 months for load forecasting with no use of any tariff plan data as done in this chapter, and Wang et al. [284] used the half-hourly load data for probabilistic load forecasting. Wen et al. [290] utilised the CER data to identify patterns of domestic power consumption. Li et al. [167] used 1896 domestic power consumption data from the days when users were charged with the standard fixed-rate tariff plan. To the author's best knowledge, none of previous works use this dataset for the same purpose of this chapter.

During the trial period households were randomly allocated to one of the four TOU tariffs (TOU-A, TOU-B, TOU-C and TOU-D) along with billing information as an incentive for load shifting. CER also collected demographic information via questionnaires to research participants, such as: gender, socioeconomic classification, age group, income level, list of appliances, internet access, number of other residents, housing type, employment status, owner/tenant, education level etc.

Four major demographic features are used in this research: gender, age group, social class, and number of other residents. In this study, the subset of 646 TOU tariff participants (households) with the same level of DSM stimuli (bimonthly bill, energy usage statement and electricity monitor) are used. Similarly, the subset of 929 households who are not assigned to any TOU tariffs are used as a *control group*.

It is possible that a weather effect might impact the differences in load profiles across the pre/post observation periods. In this regard the utilisation of a *control group*, who by definition are no different from the TOU group (apart from facing a constant flat tariff), can be used to isolate any confounding effect of this type.

In order to further rule out the impact of other changes, such as a change in consumption behaviour on our estimate of the impact of the introduction of TOU tariffs, a subset of the data around the TOU introduction on 1st January 2010 is used. Specifically, two periods of one month each are considered; December 2009 and January 2010. The number of data points for weekday and non-weekday are 44 and 18, respectively. These make it possible to analyse the pre/post-intervention effect. By limiting the period to just two months (one month pre/post the introduction of TOU tariffs), any seasonality effect should be minimised, making it easier to isolate the demand response due to the introduction of the TOU tariff.

The structure of TOU tariffs and the flat-rate tariff are presented in Table 3.1. TOU tariffs A, B, C and D have three different rates within a given weekday, and two different rates within a non-weekday (weekend and bank holidays). Peak ratios are calculated by taking the ratio of the peak time rate of weekday and non-weekday respectively to the original flat tariff rate 14.10. Household assigned to the *control group* remain on the flat tariff during the post-intervention period.

| Tariff | Flat (Control) | TOU-A | TOU-B | TOU-C | TOU-D |
|---|---|---|---|---|---|
| Off-peak | 14.10 | 12.00 | 11.00 | 10.00 | 9.00 |
| Mid-peak | 14.10 | 14.00 | 13.50 | 13.00 | 12.50 |
| Peak | 14.10 | 20.00 | 26.00 | 32.00 | 38.00 |
| Weekday peak ratio | 1.00 | 1.42 | 1.84 | 2.27 | 2.70 |
| Non-weekday peak ratio | 1.00 | 0.99 | 0.96 | 0.92 | 0.89 |

Table 3.1 Flat-rate tariff and the four TOU tariffs are used in the CER study. The values are cents per kWh. Off-peak (23:00-08:00), Mid-peak (weekdays 08:00-17:00, 19:00-23:00, non-weekdays 17:00-19:00), Peak (17:00-19:00).

## 3.3 Modelling Framework

An estimate of the impact of the TOU tariffs is obtained by comparing, for each household, the historical load profile generated under a flat tariff (pre-intervention) and the load profile under the TOU tariff (post-intervention). Although this is of interest in itself, companies and regulators will only observe historical load profiles at the point in which TOU tariffs are actually introduced into the market. In this sense the key objects that are of interest are the forecasts of the load profiles once households are offered TOU tariffs, particularly in the peak periods for weekdays, where it matters most to both consumers and energy suppliers.

Figure 3.1 summarises the key steps of the proposed modelling. Two types of input data (historical smart meter data, and demographic data) are initially prepared. The smart meter data over 62 days (December 2009 and January 2010) recorded at half-hour intervals is split into weekday and non-weekday subsets as the structure of TOU tariffs are different in the given dataset.

Once data is prepared, the statistical model is created, starting from the feature extraction. Given 646 households on one of the four TOU tariffs with 48 half-hourly electricity consumption, which are aggregated over the periods, there are 31008 data samples= $646 \times 48$ half-hour electricity consumption as input samples for the models. A description of a data sample for one household is given in Table 3.4. The outputs from the statistical model are validated using cross-validation. More details are explained in the Section 3.4.1.

The output generated from the model is an intra-day predicted load curves for each household assigned to a TOU tariff. This represents average consumption for each of the half-hour intervals averaged over the prediction period. By utilising error metrics such as MAPE with the unseen test data, model performance is evaluated (see 3.4.2).

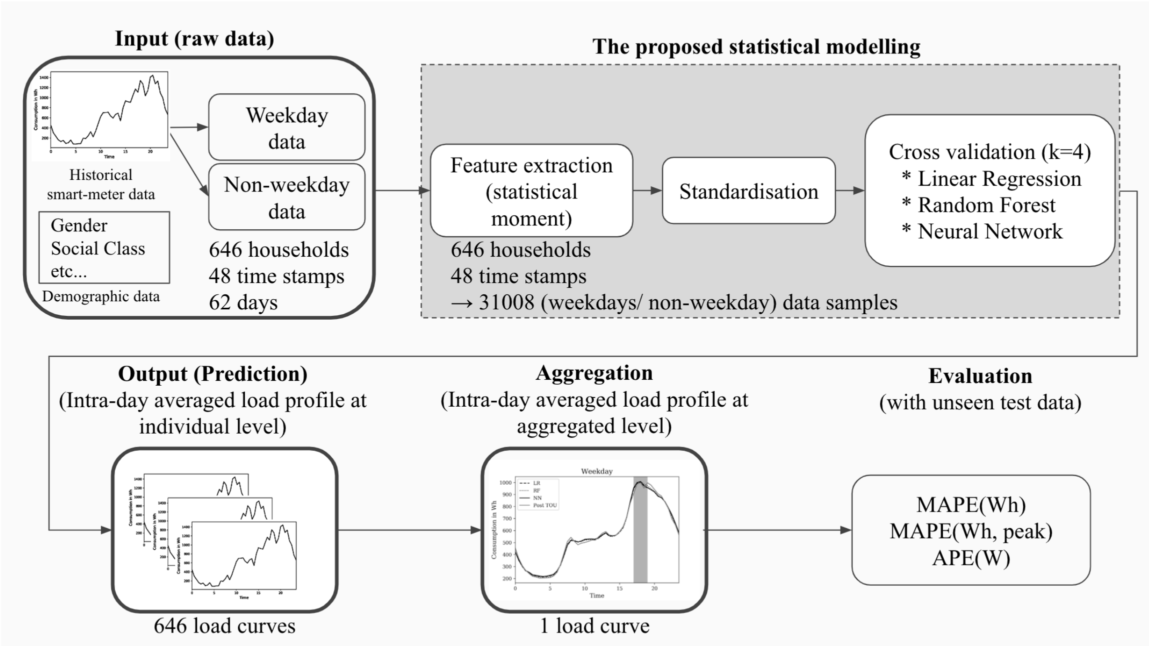
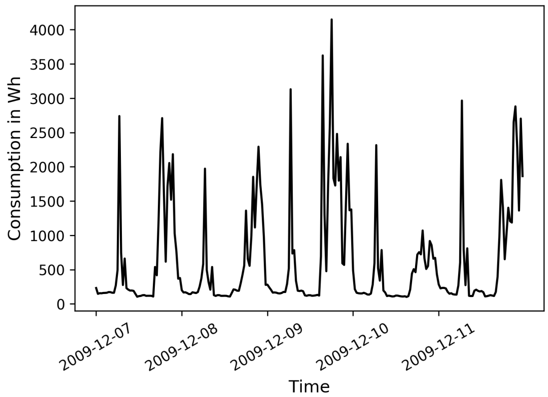



Fig. 3.1 Each step of the proposed model from the input to the performance evaluation.

### 3.3.1 Historical Consumption

At time $t$ a load history, say $c_t, c_{t-1}, c_{t-2}, \ldots$, is observed, where a given element, say $c_j$, denotes a meter reading recording the total energy consumed in a given time interval (i.e., half-hour). This time series of meter readings is then collected in a $D \times n$ matrix $\mathbf{c} = \{c_{d,\tau}\}$, where $\tau = 1, \ldots, n$ indexes the time stamps for the $d^{th}$ day. $C_\tau$ is a $D \times 1$ vector that contains the readings for the $\tau^{th}$ time stamp collected over $D$ days. If $\mathbf{c}$ is averaged along the columns then $\bar{\mathbf{C}} = \{\bar{C}_\tau\}$ is a $n \times 1$ vector, representing the average intra-day shape of the electricity demand curve under a flat tariff. $\tilde{\mathbf{C}}$ denotes a comparable object for a TOU tariff, where prices vary over the $\tau$ intervals. The consumption level during the $\tau^{th}$ interval is considered as a random variable $C_\tau$, with $\mathbf{C} = \{C_\tau\}$ a $N \times 1$ random vector.

In Figure 3.2, two plots extracted from the dataset are presented. The first presents the half-hourly consumption corresponding to five consecutive weekdays of electricity usage for a given customer; each dot represents the consumption measured in a given half-hour. The second plot shows the historical load profile, $\bar{\mathbf{C}}$ ($D$ = 5), representing the average half-hour consumption over the same five weekdays.



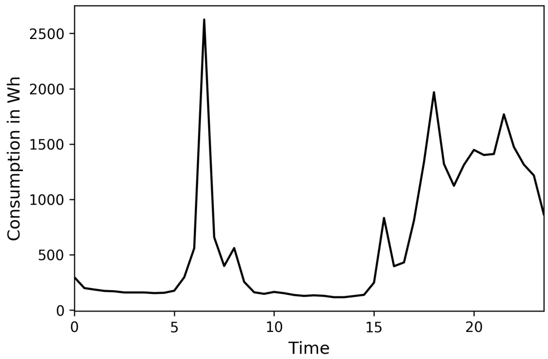




Fig. 3.2 Left: half-hourly electricity consumption for five consecutive days for a particular user. Right: Average intra-day electricity demand curve over the same five weekdays.

### 3.3.2 Statistical Description of Lifestyle

Making inference on consumer lifestyle patterns using smart meter data is a critical component of energy efficiency programs and other services. Recently, Beckel et al. [23] inferred household characteristics from electricity consumption data by using statistical models with a large number of features such as average consumption during different times of the day, features related to temporal dynamics, and the first ten principal components (Wold et al. [295]). However, the feature construction processes could be improved accordingly. First, the importance of each feature to the model performance is not examined. Second, some popular metrics in statistics, such as the moments of a distribution, which are frequently used to capture the shape of a distribution (see the study by Press et al. [223]), are not used. An advantage in the use of statistical moments is that it compresses all the information contained in the data into a very small number of expressions. This study utilises the first four moments: mean, variance, skewness and kurtosis, measuring their importance for the model performance, and comparing against other demographic characteristics.

For each time stamp $\tau$, the $n$th moment is derived as

$$\mu_n(c_\tau) = \sum_{d=1}^{D} (c_{d,\tau} - \bar{C}_\tau)^n p_\tau(c_{d,\tau}) \tag{3.1}$$

where $p_\tau(c)$ is the probability of having consumption $c$ at the time stamp $\tau$. In the context of the residential electricity consumption, each moment indicates a particular aspect of consumer behaviour. In this study, the time stamp $\tau$ represents a half-hourly period between midnight ($\tau = 0$) and 11:30pm ($\tau = 47$).

Figure 3.3 illustrates average consumption $\bar{C}_\tau$ of a single household at four different time stamps ($\tau = 0, 12, 24, 36$) during weekdays at the pre-intervention period (December 2009), and Table 3.2 presents the values for the moments. $\bar{C}_\tau$ is highest at 18:00, and lowest at midnight 0:00. A high variance $\mu_2(c_\tau)$, indicates that consumption at time stamp $\tau$ is relatively unpredictable. As expected, in this example consumption is more variable at 12:00 and 18:00 than during the time interval 0:00−6:00. Skewness $\mu_3(c_\tau)$ is a measure of the lopsidedness of the distribution. A distribution having a longer tail on the right will have a positive skewness. This household has a high value of $\mu_3(c_\tau)$ at 12:00 (see Table 3.2). Hypothetically, this statistical characteristic reflects occasional energy-intensive activities at midday such as cooking and laundry. Finally, $\mu_4(c_\tau)$ kurtosis, is a measure of the heaviness of the tail of the distribution, compared to the normal distribution of the same variance is presented. The values at 0:00 and 6:00 are much lower than during the day, implying the night-time electricity consumption pattern (most likely sleeping based on low consumption) is consistent. In summary, these statistical features of load profiles could reflect valuable information about household behaviour based on their own past consumption.

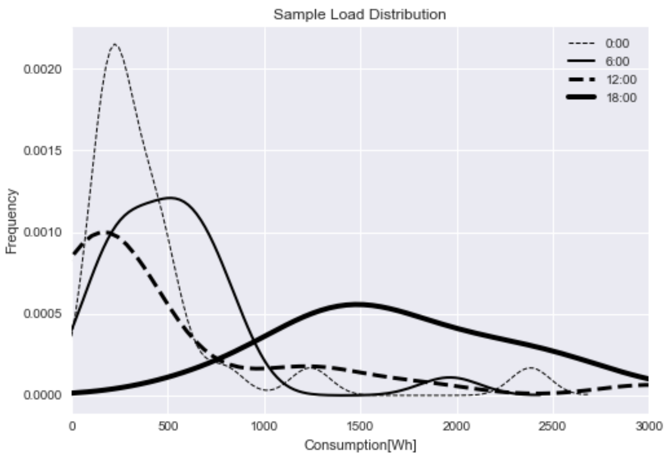



Fig. 3.3 Consumption distribution of a single household at different time stamp $\tau$ ($\tau = 0, 12, 24, 36$) during weekdays at the pre-intervention period (December 2009).

| Time | 0:00 | 6:00 | 12:00 | 18:00 |
|---|---|---|---|---|
| $\bar{C}_\tau$ | 445 | 527 | 689 | 1870 |
| $\mu_2(c_\tau)$ [$\times 10^5$] | 2.30 | 1.43 | 10.6 | 6.72 |
| $\mu_3(c_\tau)$ [$\times 10^8$] | 3.32 | 1.20 | 24.0 | 6.51 |
| $\mu_4(c_\tau)$ [$\times 10^{11}$] | 6.34 | 1.91 | 80.0 | 18.6 |

Table 3.2 Moments of the consumption distribution (in Wh) of a single household at different time stamp $\tau$ ($\tau = 0, 12, 24, 36$) during weekdays at the pre-intervention period (December 2009).

### 3.3.3 List of Variables

Table 3.3 summarises the variables used in this analysis. The target variable[2] $\tilde{C}_\tau$ denotes average consumption in Wh under a TOU tariff at time stamp $\tau$, a half-hourly period between midnight ($\tau = 0$) and 11:30pm ($\tau = 47$). Variables $\bar{C}_\tau$, $\mu_2(c_\tau)$, $\mu_3(c_\tau)$, and $\mu_4(c_\tau)$ are used for training and are therefore calculated over the training period (December 2009); $\tilde{C}_\tau$ is averaged over the evaluation period (January 2010).

The variables used for model development are categorised into three feature groups (FG)s depending on the nature of the parameters. The first FG includes the first four statistical moments. Each variable $\bar{C}_\tau$, $\mu_2(c_\tau)$, $\mu_3(c_\tau)$ and $\mu_4(c_\tau)$ are standardised by subtracting the mean from each feature and dividing by its standard deviation. This technique has been confirmed effective in feature selection by Dy and Brodley [72]. The second FG includes tariff information including rates under the flat and the TOU tariffs, and the peak ratio. The third FG has the four demographic features, and the definitions of the each feature are described in Table 3.3.

[2]The target has 48 values since this model is interested in forecasting intra-day load profile at every half-hour point averaging over days.

| Group | Variable | **Number of possible values** | **Description** |
|---|---|---|---|
| | $\tau$ | 48 | Represents a half-hourly period between midnight (0) and 11:30pm (47) |
| 1 | $\bar{C}_\tau$ | Continuous | Mean |
| 1 | $\mu_2(c_\tau)$ | Continuous | Variance |
| 1 | $\mu_3(c_\tau)$ | Continuous | Skewness |
| 1 | $\mu_4(c_\tau)$ | Continuous | Kurtosis |
| 2 | Flat price | Continuous | Tariff rate given a specific time under flat tariff |
| 2 | TOU price | Continuous | Tariff rate given a specific time under TOU tariff |
| 2 | Peak ratio | Continuous | A ratio of the peak time rate to the average rate. |
| 3 | Age group | 5 | 0:26-35, 1:36-45, 2:46-55, 3:56-65, 4:65+ |
| 3 | Gender | 2 | 0:Female, 1:Male |
| 3 | Socioeconomic classification | 6 | AB, C1, C2, DE, F, Refused |
| 3 | Other living residents | 3 | 0:Only adults, 1:Adults and children, 2:None |
| | $\tilde{C}_\tau$ | Continuous | Average consumption in Wh under a TOU tariff (target variable). |

Table 3.3 List of variables utilised in this analysis.

Table 3.4 illustrates that the form of a data sample for a given household comprises the variables described in Table 3.3. Note that $\bar{C}_\tau$, $\mu_2(c_\tau)$, $\mu_3(c_\tau)$ and $\mu_4(c_\tau)$ are standardised and $\tilde{C}_\tau$ is not.

| $\tau$ | $\bar{C}_\tau$ | $\mu_2(c_\tau)$ | $\mu_3(c_\tau)$ | $\mu_4(c_\tau)$ | Flat price | TOU price |
|---|---|---|---|---|---|---|
| 13 | 0.615 | 0.483 | 0.078 | -0.015 | 14.1 | 12.0 |

| Peak ratio | Age group | Gender | Socioeconomic classification | Other living residents | $\tilde{C}_\tau$ |
|---|---|---|---|---|---|
| 1.67 | 4 | 0 | C2 | 2 | 801 |

Table 3.4 One sample data of a household.

### 3.3.4 Performance Metrics

Cappers et al. [36] used two different performance metrics to evaluate demand response performance: the one compares the actual load reduction to what was initially subscribed to a demand response program, and the other one estimates the customer's actual demand response load curtailment compared to their peak demand. Similarly in physics, *Energy* and *Power* are two major metrics for quantifying the status of electricity: *Energy* is the product of power and time (measured in Watt-hours), and *Power* is the flow of energy at any one time and is measured in Watts (W). Therefore, to indicate the peak reduction in *Energy* and *Power*, the following two metrics $\mathrm{R}_{peak}$ and $\mathrm{R}_{peak}(W)$ are used for this work respectively:

$$\mathrm{R}_{peak} = \frac{1}{n_{peak}} \sum_{\tau \in Peak} \frac{\bar{C}_{\tau}^{avg} - \tilde{C}_{\tau}^{avg}}{\bar{C}_{\tau}^{avg}}, \tag{3.2}$$

$$\mathrm{R}_{peak}(W) = \frac{\max_{\tau \in Peak} \bar{C}_{\tau}^{avg} - \max_{\tau \in Peak} \tilde{C}_{\tau}^{avg}}{\max_{\tau \in Peak} \bar{C}_{\tau}^{avg}} \tag{3.3}$$

where $\tilde{C}_{\tau}^{avg} = \frac{1}{M} \sum_{m=1}^{M} \tilde{C}_{\tau}^{(m)}$, $M$ denotes the number of households, $\bar{C}_{\tau}^{avg}$ is the observed average consumption. $n_{peak}$ is the number of intervals that correspond to peak time ($n_{peak} = 4$).

### 3.3.5 Preliminary Analysis

A peak reduction effect could be influenced by a number of factors such as weather conditions and changes of occupancy behaviour. Limiting the observed period to two months (one month each for pre/post TOU tariff intervention) minimises these external influences. We also compare the load profiles of the *control group* who remain on the flat tariff during the two periods, to evaluate the potential of these factors to confound our estimate of the impact of the introduction of TOU tariffs on average load profiles.

Figure 3.4 presents the average consumption profiles of TOU and the *control group* during the pre/post intervention period; Table 3.5 summarises the peak reduction of each group relative to the benchmark period. The electricity consumption of the *control group* remains unchanged during weekdays, and shows a slight increase during the weekends, whereas all TOU groups show the significant peak reduction during the peak time.

An independent t-test is conducted to compare the differences in the consumption between the pre and post observation periods for TOU and the *control group* for weekday data. As a result, for the TOU group, there was a significant difference in the peak consumption during the pre/post intervention periods ($p_{\text{value}} = 9.9 \times 10^{-6}$), while there wasn't for the *control group* ($p_{\text{value}} = 0.91$).

This result concludes that there are no external factors that brings the peak reduction during the observation periods, and the TOU tariff price signals is considered to be the sole factor to realise the peak reduction.

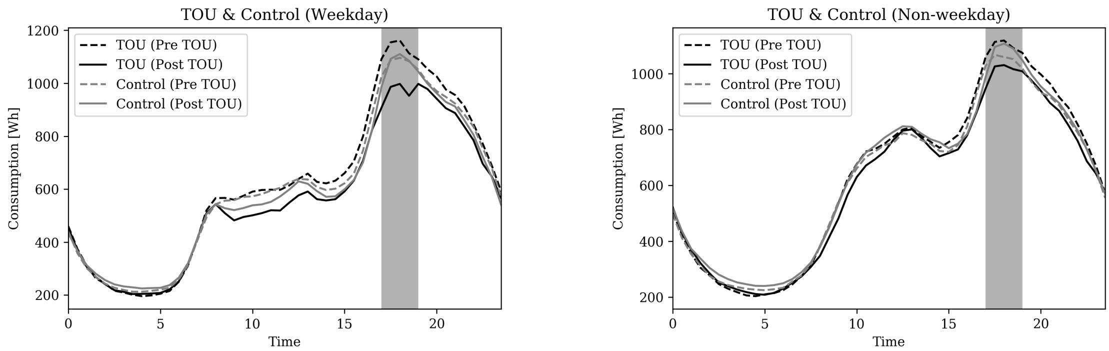



Fig. 3.4 Comparison of average consumption profiles between the TOU group and the *control group*

The extent of load shifting for the TOU tariff participants is generally consistent with the relative magnitude of incentives given by the peak ratios. Customers assigned to TOU tariff D, who are given the highest incentive for load shifting, reveal the largest demand response with a 16.77% energy reduction and 15.79% power reduction during the weekdays. During the non-weekdays the reduction is smaller for all tariffs, and consistent with the relative low peak ratio.

| Date type | Metric | Control | TOU-A | TOU-B | TOU-C | TOU-D |
|---|---|---|---|---|---|---|
| Weekday | $R_{peak}$ | -0.3 % | 12.41 % | 12.10 % | 12.46 % | 16.77 % |
| Weekday | $R_{peak}(W)$ | -1.3 % | 13.43 % | 13.13 % | 12.72 % | 15.79 % |
| Non-weekday | $R_{peak}$ | -3.4 % | 6.31 % | 10.76 % | 6.59 % | 7.11 % |
| Non-weekday | $R_{peak}(W)$ | -3.8 % | 7.60 % | 12.25 % | 8.62 % | 7.67 % |
| | Number of households | 929 | 230 | 93 | 233 | 90 |

Table 3.5 Overall mean of peak-load reduction.

Figure 3.5 observes that the distribution of peak reduction is widely spread at the individual level across the four tariffs; 265 out of 646 households (41.0%) actually increased peak consumption despite the penalised peak rate. This indicates that individual load consumption does not necessarily react to a TOU tariff, although the aggregated load over the same TOU tariff group reacts more rationally to minimise the energy bill (Table 3.5 shows that all tariff groups achieved both *Energy* and *Power* reduction at the aggregated level). Therefore the impact of TOU tariff should be examined at the aggregated scale.

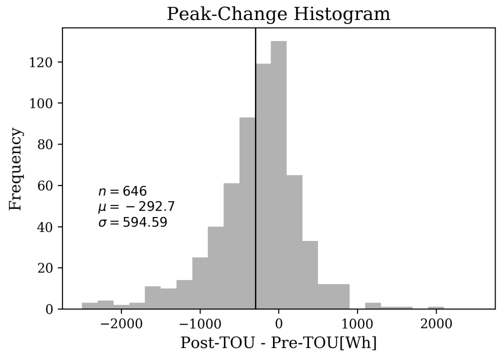



Fig. 3.5 Peak-change at the individual level after an introduction to a TOU tariff.

## 3.4 Modelling Techniques

This work utilises three common predictive modelling techniques for load forecasting: LR, ANN and DT. Predictive modelling seeks to locate rules for predicting the values of one or more variables in a data set (outputs) from the values of other variables in the data set (inputs). These inputs and outputs are the energy consumption data described in Section 3.2.

The popularity of the LR model may be attributed to the simplicity and interpretability of model parameters. Traditionally, this approach has been the most popular modelling technique for utility companies in predicting energy consumption. Ranjan and Jain [228] demonstrated the application of linear regression models of energy consumption for different seasons in Delhi. Similarly, Al-Garni et al. [7] analysed in Eastern Saudi Arabia, and Tso and Yau [271] did in Hong Kong.

ANNs somewhat mimic the learning process of a human brain. Instead of complex rules and mathematical routines, ANNs are able to learn the key information patterns within a multidimensional information domain. Kalogirou and Bojic [148] explained the two key advantages of ANNs in the context of energy prediction. First, ANNs operate like a "black box" model, requiring no information about the system, such as functional form. Instead, in keeping with a machine learning approach, the ANN learns the relationship between the input parameters and the controlled and uncontrolled variables by studying historical data. Another advantage is their ability to handle large and complex systems with many interrelated parameters. The success of ANNs is based, in part, on an ability to ignore input data that are of minimal significance and concentrate instead on the more important inputs.

DT is a non-parametric supervised machine learning method which partitions the data into "leaves" defined by covariates in order to estimate the individual outcomes. DT is constructed by recursively splitting the data in order to minimise the mean square error of estimated outcomes. The method can then be used to predict the value of a target variable utilising simple decision rules learned from the data features. The algorithm used in this work is CART (classification and regression trees) (Quinlan [226]).

Model selection, which in the case of decision trees is the partition that defines the tree, and estimations are carried out on the training data with the goal of minimising expected mean squared error in the "holdout" or "test" data. In some cases the selection and estimation of a model also requires a choice of value for one or more tuning parameters. The model conducts a grid search over the maximum depth, whose effectiveness to avoid over-fitting the model to the training dataset has been shown by Safavian and Landgrebe [235].

In this analysis, 22944 samples, each of which denotes a datum of a single household at a given time stamp, are generated from 48 half-hour data samples of 646 households as training data (see Section 3.4.1). These samples, combined with the 12 features outlined in Table 3, are used to predict the target variable $\tilde{C}_\tau$. An example of a tree is illustrated with the setting of maximum depth of 2 in Figure 3.6. [3] The samples in the top node are partitioned using recursive binary splitting to generate the prediction in the bottom node. Features such as $X[1]$ (average consumption $\bar{C}$) are used for the binary split. In this analysis, the optimal maximum depth based upon minimum MAPE, is 30 over the range 10 to 50.

As noted by Strobl and Zeileis [257], single trees can be unstable such that small changes in the training data can lead to very different models or trees. This can be corrected by constructing a large number of DT at training time and outputting the class that is the mean prediction of the individual trees; this technique is called Random Forest (RF) (Friedman et al. [98]). Hence, this work uses RF instead of DT. Another common way of preventing this is cross-validation as discussed by Sterlin [255]. This will be explained in the following section.

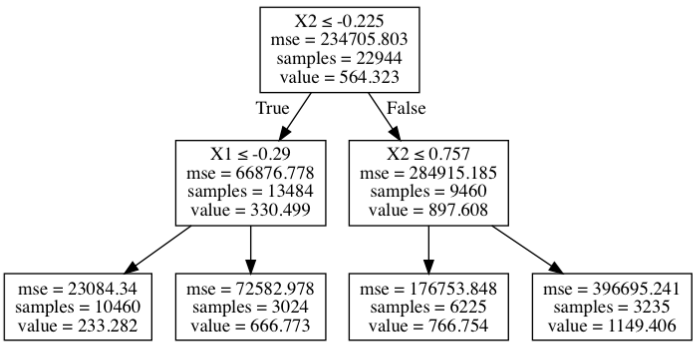



Fig. 3.6 An example decision tree with the setting of maximum depth of 2.

[3] A larger number for maximum tree depth generates more granular predictive values.

### 3.4.1 Cross Validation

As standard in statistical modelling, k-fold cross validation, whose success in accuracy estimation has been reported by Kohavi et al. [158], is used to check the accuracy of model outputs by splitting the data across all tariffs into four equal subsets: three for training and one for testing. All data samples are split into four groups so that each subset volume is almost equal for each tariff (see Figure 3.7).

The cross validation process is repeated four times ($k = 4$), so each subset of the data is used once for validation purposes. As a result, 646 load curves are predicted from the four folds. These results are then averaged to give a single estimation for each time period.

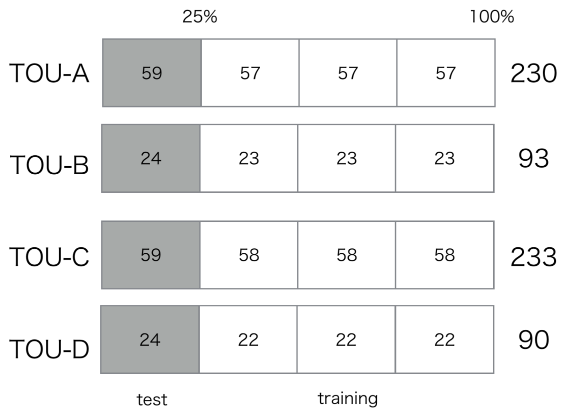



Fig. 3.7 Test and training samples for k-fold cross validation ($k = 4$).

### 3.4.2 Evaluation Measures

The model accuracy is evaluated using Mean Absolute Percentage Error (MAPE), the measure most frequently used to assess the performance of a model in the field of a medium-term load forecasting such as the study by Hahn et al. [118]. The main objective is to minimise the MAPE over household groups, and particularly during the peak time. Two MAPE metrics are used:

$$\text{MAPE}_g^i = \frac{1}{n}\sum_{\tau=1}^{n}\left|\frac{\tilde{C}_\tau^{avg} - \hat{C}_\tau^{avg}}{\tilde{C}_\tau^{avg}}\right|, \tag{3.4}$$

$$\text{MAPE}_{g,peak}^i = \frac{1}{n_{peak}}\sum_{\tau \in Peak}\left|\frac{\tilde{C}_\tau^{avg} - \hat{C}_\tau^{avg}}{\tilde{C}_\tau^{avg}}\right|, \tag{3.5}$$

where $\tilde{C}_\tau^{avg} = \frac{1}{M}\sum_{m=1}^{M}\tilde{C}_\tau^{(m)}$, $M$ denotes the number of households, $i$ indexes the cross validation fold, $m$ indexes households, $\tilde{C}_\tau^{avg}$ is the observed average consumption, and $\hat{C}_\tau^{avg}$ is the prediction made with the proposed model. $n$ is the number of half-hour intervals and $n_{peak}$ is the number of intervals that correspond to the peak time ($n = 48$, $n_{peak} = 4$).

In addition to MAPE, Absolute Percentage Error (APE) is used to measure the model's power(W) prediction. APE is calculated as,

$$\text{APE}^{i}_{g,peak}(W) = \left| \frac{\max_{\tau \in Peak} \tilde{C}^{avg}_{\tau} - \max_{\tau \in Peak} \hat{C}^{avg}_{\tau}}{\max_{\tau \in Peak} \tilde{C}^{avg}_{\tau}} \right|. \tag{3.6}$$

Given $k = 4$ cross validation, the average across the folds is taken as the final $\text{MAPE}_g$, $\text{MAPE}_{g,peak}$ and $\text{APE}_{g,peak}$.

## 3.5 Results

Table 3.6 presents estimates of MAPE for the three different techniques (LR, NN and RF). The RF model outperforms LR and NN for both values of MAPE, especially in terms of $\text{MAPE}_{g,peak}$ during the weekdays, which is the main performance indicator. In forecasting average load for a group of households RF model yields a MAPE value of 2.05% for the weekday and 1.48% for the weekday peak time.

| Date type | Model | LR | RF | NN |
|---|---|---|---|---|
| Weekday | $\text{MAPE}_g$ | 2.95% | 2.05% | 3.12% |
| Weekday | $\text{MAPE}_{g,peak}$ | 1.78% | 1.48% | 1.94% |
| Weekday | $\text{APE}_{g,peak}(W)$ | 0.60% | 0.13% | 0.58% |
| Non-weekday | $\text{MAPE}_g$ | 7.65% | 2.66% | 6.15% |
| Non-weekday | $\text{MAPE}_{g,peak}$ | 0.77% | 1.61% | 0.25% |
| Non-weekday | $\text{APE}_{g,peak}(W)$ | 0.64% | 1.69% | $3.0 \times 10^{-4}$% |

Table 3.6 Comparison of the three statistical models on test data

In using MAPE as a standardised measure of model performance the proposed model compares favourably relative to existing medium-term forecast studies with a similar forecasting time horizon. Pedregal and Trapero [216] demonstrated a comparable finding with a MAPE varying between 5% to over 10% based upon medium-term(12 week ahead) hourly electricity forecasting at an aggregated level. Al-Hamadi and Soliman [8] presented a model to forecast weekly average intra-day load profile with a time-horizon of a year, delivering the result that the MAPE is 3.8%. Given that this forecasting problem includes the demand response following the introduction of a TOU tariff, this model incorporates additional complexity compared to other existing medium-term load forecasting studies. In this respect the accuracy of the proposed model is competitive in medium-term load forecasting models, and should be of practical use for decision making to assess the medium-term impact of load adjustment to TOU.

Figure 3.8 presents the intra-day load profiles across the different models. As a reference point, the line of the actual post-intervention load profile (labelled as 'Post-TOU', averaged load curve in January 2010) is also given. All three models forecast the peak reduction closely.

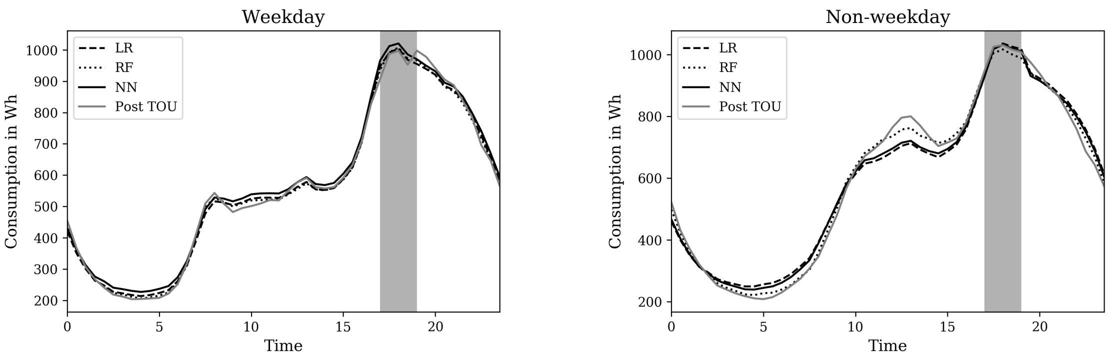



Fig. 3.8 Comparison of post- TOU load predictions using three different statistical techniques.

Figure 3.9 shows the prediction errors between post-intervention load profile and each prediction. LR and NN have most of their errors at the border of the peak time where abrupt behavioural changes have been observed. The results consistently favour RF as the preferred modelling technique.

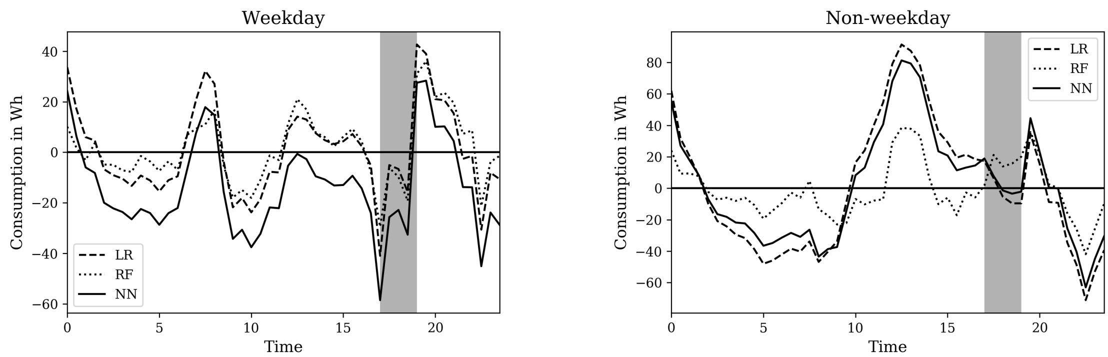



Fig. 3.9 Prediction error in Wh between actual load profile subsequent to an introduction of TOU tariffs, and predicted load profiles for three different statistical techniques.

### 3.5.1 Feature Importance

DT model results provide clear information on the importance of significant factors for prediction based on Gini coefficient (Breiman [29]). In regression analysis, its value is calculated as

$$G = \sum_{i=1}^{n} p_i(1 - p_i), \tag{3.7}$$

where $n$ represents the number of total "leaves" and $p_i$ is the ratio of the $i$th leave.

The importance of a feature is computed as the (normalised) total reduction of the criterion that is attributable to that feature. Table 3.7 reports this importance of the RF model. The higher the rating, the more important the feature. Every time a split of a node is made on variable $m$ the Gini impurity criterion for the two descendent nodes is less than the parent node. Summing the decreases in the Gini measure for each individual variable over all trees in the forest gives a variable importance that is often very consistent with the permutation importance measure (Breiman and Cutler [30]).

The work finds that the average consumption feature is the most important predictor. It is also noteworthy that the most relevant features are statistical features of consumption, suggesting the tree strongly uses these features to forecast the load shifting. Although the feature TOU price, and peak ratio does not have an influential effect in this model, it is important to remember that the window of the peak period of four TOU tariffs is fixed under this trial, so that the effectiveness of these two features might be underestimated. Therefore, further trials with different windows of peak periods is needed to examine the importance of these parameters.

| Feature | Importance |
|---|---|
| average | 66.77% |
| kurtosis | 9.87% |
| time | 8.61% |
| skewness | 5.79% |
| variance | 5.73% |
| TOU price | 0.90% |
| other living residence | 0.65% |
| age group | 0.62% |
| social class | 0.59% |
| peak ratio | 0.27% |
| gender | 0.19% |

Table 3.7 Features importance according to RF. These variables are summarised in table 3.3

An additional important finding is that none of the demographic features generate a significant contribution to the predictive capacity. Eliminating these features with low importance values could improve the model performance. This method of feature selection has been utilised by a number of studies. Granitto et al. [114], for instance, has introduced random forest recursive feature elimination to determine small subsets of features with high discrimination levels on chemical dataset. Díaz-Uriarte and De Andres [65] has also applied this technique for gene selection.

Table 3.8 shows the RF model performance with/without demographic variables. It should be noted that the absence of demographic information does not lead to a deterioration in model performance, and the model even works better. A recent study of electric behavioural analyses conducted by O'Neill and Weeks [208] similarly observed the similar effect. This finding removes the extra cost for energy companies and analysts since the collection of demographic data is costly, with a limited ability to increase the predictive ability of a given model.

| Date type | Model | With demographic | Without demographic |
|---|---|---|---|
| Weekday | $\text{MAPE}_g$ | 2.05% | 1.80% |
| Weekday | $\text{MAPE}_{g,peak}$ | 1.48% | 1.11% |
| Weekday | $\text{APE}_{g,peak}(W)$ | 0.14% | 0.05% |

Table 3.8 Comparison of the RF model performance with/without demographic features

### 3.5.2 Prediction of Intra-day Load Profile

The actual and predicted intra-day load profile generated by the RF model are presented in Figure 3.10. The results demonstrate that for the peak periods the model successfully captures the behavioural change for all tariffs.

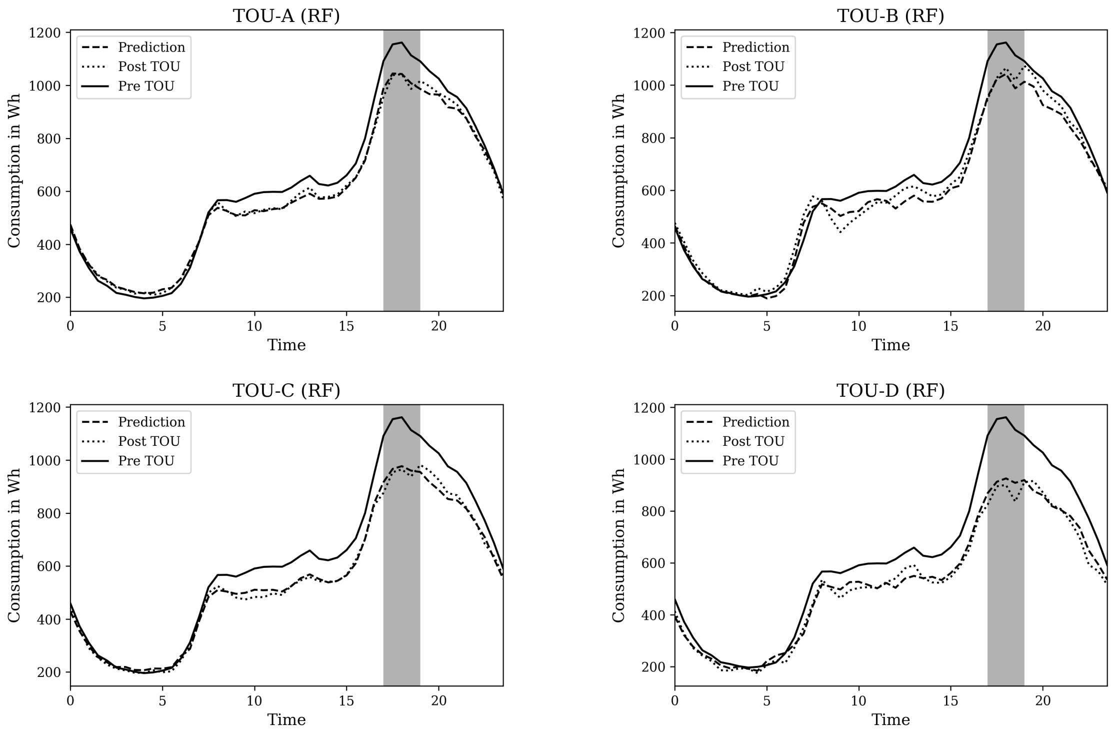



Fig. 3.10 ‘Pre-TOU’ and ‘Post-TOU’ actual load under the flat-rate tariff and a TOU tariff respectively. ‘Prediction’ is predicted load curve by this model.

The difference between ’Post-TOU’ predictions and actual load are demonstrated in Figure 3.11 for each group. These lines are more irregular than the similar analysis in Figure 3.9, since users are divided into the four tariff groups, where the number of households in each group is relatively small. Each line shows zigzag patterns around the zero line, and no significant over/underestimation in any particular time periods or any groups has been observed. The common phenomenon observed across the four groups is the negative spike at the beginning of the peak period, and positive spike at the end of the peak period. This indicates customer demand response is not as immediate as the model predictions, with around a 30 minutes time lag prior to customer adoption. This characteristic is not captured by the proposed model, and is the source of the most significant errors in the modelling performance.

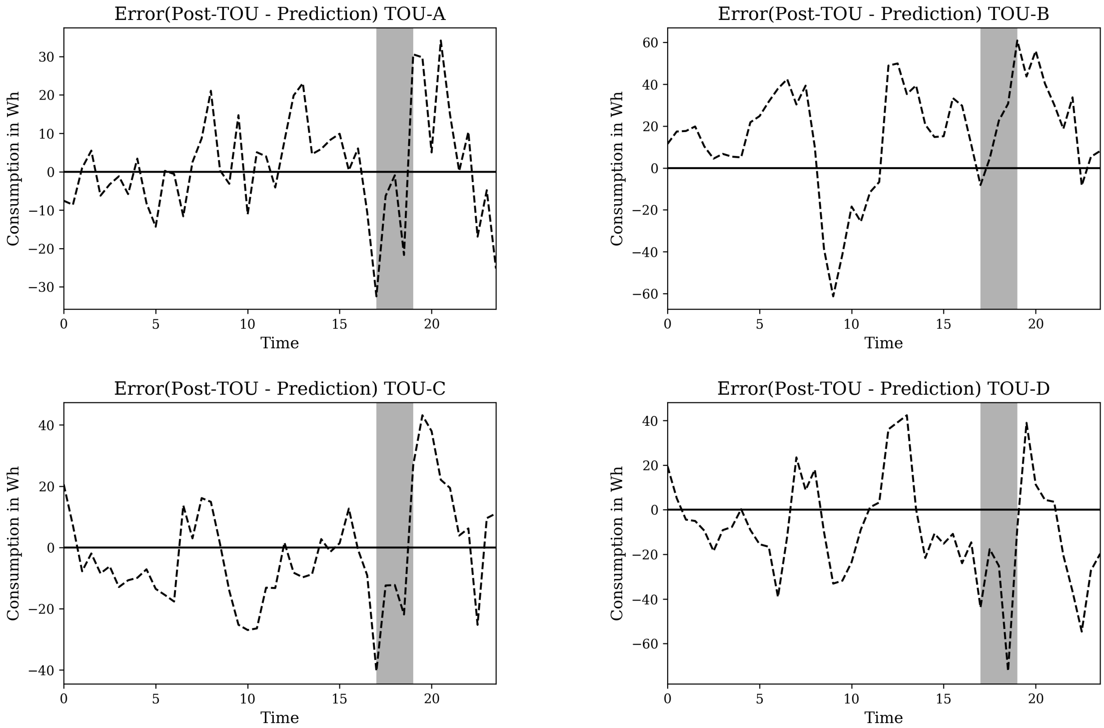



Fig. 3.11 Prediction error in Wh between actual load profile subsequent to an introduction of TOU tariffs, and predicted load profiles for the DT model.

## 3.6 Conclusion

The model developed in this study can be used to *forecast* the impact of the introduction of a TOU tariff. The novelty of this study lies in explicitly accounting for consumer variability by extracting key features from past data. By incorporating lifestyle constraints, measured by a number of functions of historical load, the proposed model is able to predict the full intra-day load profiles with low MAPE. The MAPE value in forecasting average load for a group of households with the best model RF is 2.05% for the weekday and 1.48% for the weekday peak time. Random Forest is the preferred modelling technique based upon a comparison with Neural Networks and Linear Regression. By comparing the model's accuracy against a number of important studies of medium-term load forecasting at an aggregated level, the work demonstrates that the model can be of practical use for decision making to assess the medium-term impact of load adjustment to a TOU tariff introduction.

The key findings of this chapter can be summarised as follows. First, we show that top-down statistical modelling of historical smart meter data can be used to forecast the effectiveness of a TOU tariff. This can help energy companies to design TOU tariffs and optimise energy sourcing strategy accordingly. Second, the work demonstrates that it is possible to infer key features from the statistical moments derived from historical smart meter data that capture lifestyle constraints at an individual level, and determine the shape of an aggregate load profile; no ex-ante data on demographics is required to run this model to generate this competitive accuracy. This removes the additional cost collecting demographic data, unlocking further value of the metering infrastructure without requiring any changes to the smart meters that have already been deployed.

# Chapter 4

# Winners and Losers under Time-of-Use Tariffs

## Highlights

- A continuous work on a TOU tariff modelling from Chapter 3, focusing on an effect at the individual level.
- A model to identify household outcomes under a Time-of-Use tariff
- Reliable model accuracy using historical electricity load and basic characteristics
- Published public dataset of energy consumption with online activity variables

## Collaborators

- Riku Arakawa[1] contributed to the discussion on the modelling of the proposed approach. He also helped to check the mathematical notations.

The second analysis chapter addresses the "TOU winner detection problem" and the "TOU public dataset problem", defined in Chapter 2. This chapter briefly overviews the current circumstances of a TOU tariffs implementations, and more detailed examination in existing approach to evaluate load shifting potentials in a "TOU tariff, and available public dataset before presenting the modelling works.

[1] is from Graduate School of The University of Tokyo, Information Science and Technology.

## 4.1 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 [175]. 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 [251]), 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 one hour 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. [58]). 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. [61]). The importance of this "smart" grid has been emphasised by Mathiesen et al. [182] for making a way to a future with 100% renewable energy and transport solutions. In Mathiesen and Lund [181], 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 [184] 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 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 [55]). A survey in the United Kingdom (The Brattle Group [264]) 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. [289]). Another large-scale longitudinal study in Italy (Torriti [268]) 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 €309 per metering point distributed amongst consumers, suppliers, and distribution system operators (European Commission [85]). 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 [203])). 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. [87]).

## 4.2 Motivation

Energy suppliers widely have introduced TOU tariffs to their consumers, and there has been previous work on optimal TOU tariffs design. As discussed and demonstrated in Chapter 3, energy companies could estimate the potential impacts of a TOU tariff before the large scale roll-out, thus they could find an optimal solution at the nation level. However, the investigations in Chapter 3 are conducted at the aggregated level, rather than at the individual household level. A closer examination at each household outcome from a TOU tariff deserves an extra work. The research question of this chapter is how to predict the effects of a TOU tariff at an individual consumer level using smart meter data.

The proposed work in this chapter departs from previous studies; the methodology adopts 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 [203]'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 [293] 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. [157]), 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. [52]). Any introduced tariff plan may fail if it does not take account of the customer's point of view (Eskom [82]) . 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 chapter 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. [62]). 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 [243]). Based on this, this chapter 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. [240]) dataset collected dynamic TOU readings in 2013 and the Pecan Street TOU dataset has measurements from 2013 to 2014 (Pecan Street Inc. [215]). 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 to 2013 (Ratnam et al. [229]). 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 [20]). Furthermore, it can be observed that the available datasets are from EU nations, Australia or US. Therefore, to the best of the author's 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 work 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 work 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 chapter is organised as follows. Section 4.3 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 4.4 outlines how the trial was structured and details the notable components. Section 4.5 defines the methodological approach to developing and testing the statistical model, and section 4.6 details the results of these models. Section 4.4.4 introduces the public dataset created as a result of this trial and gives details on how it may be accessed. Finally, Section 4.7 summarises the findings and offers commentary for future work.

## 4.3 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.

### 4.3.1 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. [285] 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 [231]). O'Neill and Weeks [208] 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. [116] 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. [302] 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. [162]) . A state transition matrix obtained by a large data set of load curves was used in (Wang et al. [282]) to calculate the entropy of users, which quantifies variability in usage pattern. It was found 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. [163] 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 [13] 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 [3] 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.

### 4.3.2 User Engagement

User engagement can be enhanced not only by tariff pricing (Campillo et al. [34]) but also by gamification. Gamification - the trend of employing game mechanisms and techniques in non-game contexts (Deterding et al. [63]) - 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. [149]). Popular design elements of a gamified application includes points, leader boards, rankings, virtual badges, and level status. Empirical studies on gamification (Hamari et al. [119]) 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. [62]), 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. [174]) 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. [165].) As an example, Zehir et al. [304] 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 [95] 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. [241] 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. [147]). 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 [212]). 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. [244]). In total, findings from these studies suggest that adopting gamification (e.g., employing mechanisms for showcasing the behaviour of peers) may be effective in increasing engagement and in shifting long-term energy consumption.

### 4.3.3 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. [172]). 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. [281]'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 [49]), 5567 households in London, United Kingdom (Schofield et al. [242]), 40 households in Austin, Texas (US) (Smith [252]) 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 [18]) and some are producing the data artificially (Li et al. [168]). However, reference real-world data sets play an important role in making research more comparable and usable.

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. [179]), 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 [166]), CalTech 101 (Fei-Fei et al. [92]), and the PASCAL challenge (Everingham et al. [86]). Wagner et al. [278] pointed out the scarcity of publicly available data in the energy disaggregation field, and created a public data set to support this research.[2]

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

## 4.4 Time-of-Use Trial

Energy market reform was implemented in Japan from 2016, where the electricity market was deregulated and competition was introduced (Shinkawa [248]). Japan is the fourth largest market in electricity consumption after China, United States and India (according to the CIA [1]), 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

[2]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.

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 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 [171]) by Looop Inc. and SMAP Energy.[3]

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 4.1). 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 4.4.2). A limited amount of demographic information - specifically household type and number of residents - was collected via a questionnaire.

| 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 |

Table 4.1 Users on TOU/Flat tariff

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.

### 4.4.1 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 [145]) tends to be high due to increased usage of air-conditioning. Figure 4.1 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

[3]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 [250]), and researchers at the University of Cambridge.

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.

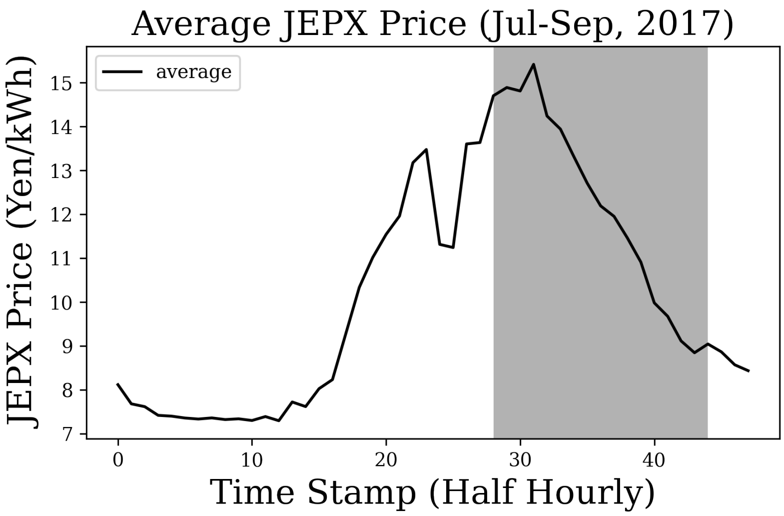



Fig. 4.1 Intra-day averaged price of JEPX spot market between July 2017 and September 2017. The horizontal axis is half-hourly time stamp from 0 (midnight) to 47 (23:30). The highlighted hours (2pm to 10pm) are the peak hours in this trial.

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

| 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 | |

Table 4.2 Tariff structure of flat and TOU tariff. Peak time is 2pm to 10pm weekdays, and off-peak time is the rest including weekends.

### 4.4.2 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.

Figure 4.2 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.

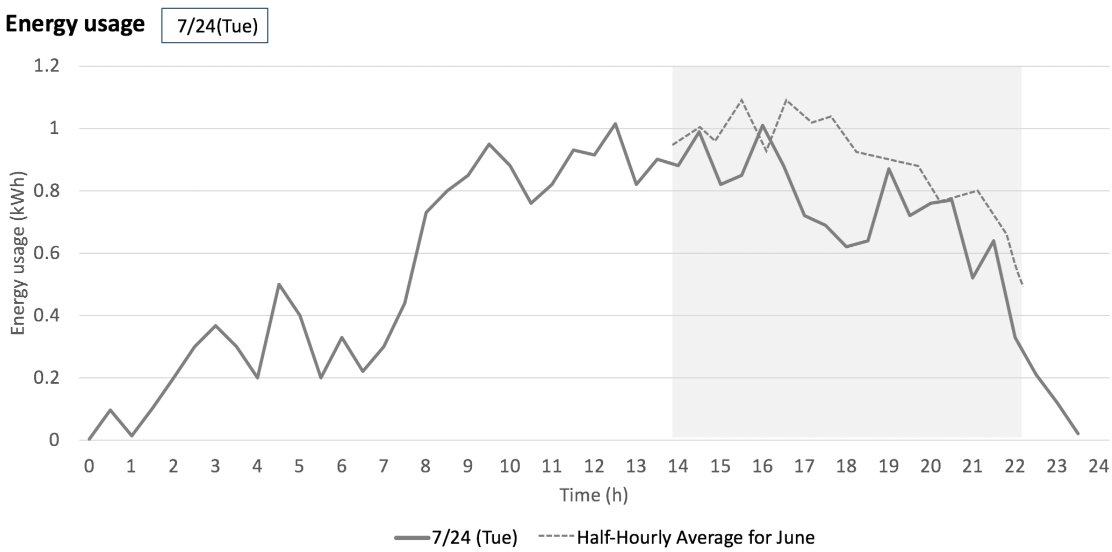



Fig. 4.2 Individual feedback and reward system.

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 0.01kWh. 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 number of measures of user activity on the web application using *Google Analytics* (Google Analytics [111]). These measures are defined as follows (Analytics Help [14]).

- Number of sessions: A session represents individual activities within the web application (checking the charts, viewing different pages, etc.) within a 30 minute window. A single user can open multiple sessions in a day. A session ends after 30 minutes 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.

### 4.4.3 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.

Figure 4.3 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 Figure 4.3).

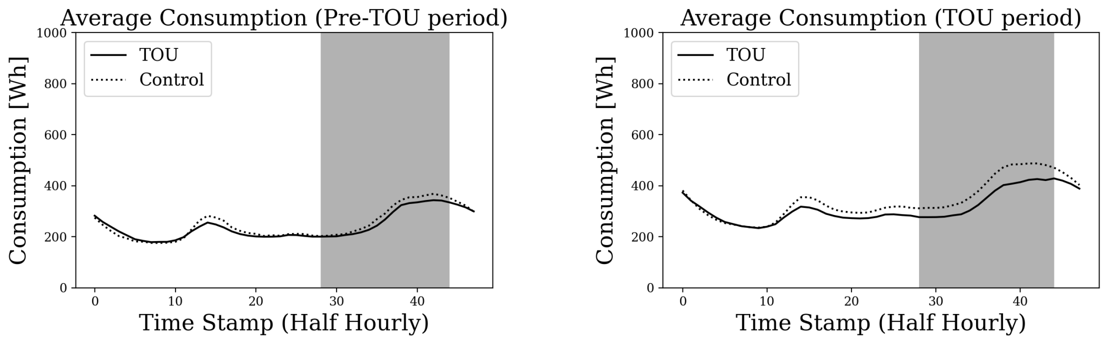



Fig. 4.3 Load curve of average consumption in TOU and control groups. (left: pre-TOU period, right: during-TOU period)

### 4.4.4 Public Dataset

The dataset used in this work has been published and is publicly available on the web: https://github.com/smapenergy/CAMSL. The CAMSL dataset contains the items shown in Table 4.3. The dataset is available for free for both academic and industrial researchers to access upon the request.

| 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 (**(author?)** [Japan Meteorological Agency]) |
| 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 |

Table 4.3 Items in the CAMSL TOU dataset

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.

## 4.5 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. [122] and Hahn et al. [118]). Here the primary objective is to train a model that minimises the loss between the predicted and actual values in a test dataset [70]. In constructing a load prediction model for individual customers under a TOU intervention, Chapter 3 (published as Kiguchi et al. [152]) found that a Random Forest (RF) model (Breiman and Cutler [30]) 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 [257]).

This work builds on Chapter 3, 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 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 work.

### 4.5.1 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

$$\tilde{R}_i = 100 \times \frac{1}{n_p} \sum_{\tau \in Peak} \frac{\bar{C}^d_{\tau,i} - \bar{C}^p_{\tau,i}}{\bar{C}^p_{\tau,i}}, \tag{4.1}$$

where $\tau$ 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 hours). $\bar{C}^p_{\tau,i}$ denotes the average consumption of the user $i$ at time stamp $\tau$ over the pre-TOU period (30 days in June 2018); $\bar{C}^{d}_{\tau,i}$ 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. [4]

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

$$R_i = \tilde{R}_i - \tilde{R}_c \tag{4.2}$$

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

$$\tilde{R}_c = \frac{1}{n_c} \sum_{i \in C} \tilde{R}_i, \tag{4.3}$$

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 noted in Chapter 3, 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

$$S_{k,i} = \begin{cases} 1 & \text{if } R_i \geq k \\ 0 & \text{else} \end{cases} \tag{4.4}$$

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

### 4.5.2 Modelling Method

The modelling method uses a RF based regression approach that estimates $R_i$, and then generate $S_{k,i}$ using (4.4). The individual level input variables are categorised into two groups:

[4] This represents the same methodology as used in the 2011 Irish TOU trial (Commission for Energy Regulation [49])

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.

Chapter 3 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 $\frac{1}{48}\sum_{\tau=1}^{48}\bar{C}^{p}_{\tau,i}$. 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 4.4.

| Group | No. | Average | Variance | Skewness | Kurtosis |
|---|---|---|---|---|---|
| TOU | 1023 | 120.1 | 685.1 | $1.49 \times 10^4$ | $1.05 \times 10^6$ |

Table 4.4 The four statistical moments of the daily consumption data in pre-TOU period.

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.

### 4.5.3 Evaluation

The introduction of $S_{k,i}$ turns this regression problem into a binary classification problem. A commonly used performance measure for binary classification[5] is defined as the total number of the correctly classified observations divided by the total sample size, namely

$$\text{ACCURACY} = \frac{TP+TN}{TP+TN+FP+FN}. \tag{4.5}$$

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

Beckel et al. [23] advocate the use of the Matthews Correlation Coefficient (MCC) over simple precision or recall when the number of samples in given classes are imbalanced in

[5]See Sokolova and Lapalme [253] for an extensive overview of different performance measures for classification tasks.

binary classification tasks. MCC utilises a penalty function to reward true positives (the underrepresented class). MCC is given by

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{4.6}$$

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 work uses MCC to quantify the performance of the classifiers.

## 4.6 Results

In this section, the classification performance of the model is examined. Section 4.6.1 evaluates the overall model performance, and discusses the potential benefit of this model In Section 4.6.2 individual feature importance is examined, and essential variables for the model construction are identified. In Section 4.6.3, 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 chapter, and gamification is a key tool to enhance the level of online engagement with marginal financial cost.

### 4.6.1 Model Results

In Figure 4.4 the distribution of $\widehat{R}_i$ 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 $\widehat{R}_i > 0$, 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 ($\widehat{R}_i > 0$) versus 742 observed. The mean of $\widehat{R}_i$ and $R_i$ are 15.9 and 16.5 kWh per day. The variance of $\widehat{R}_i$ 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 $\widehat{R}_i$ 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 chapter.

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 [47]) 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.

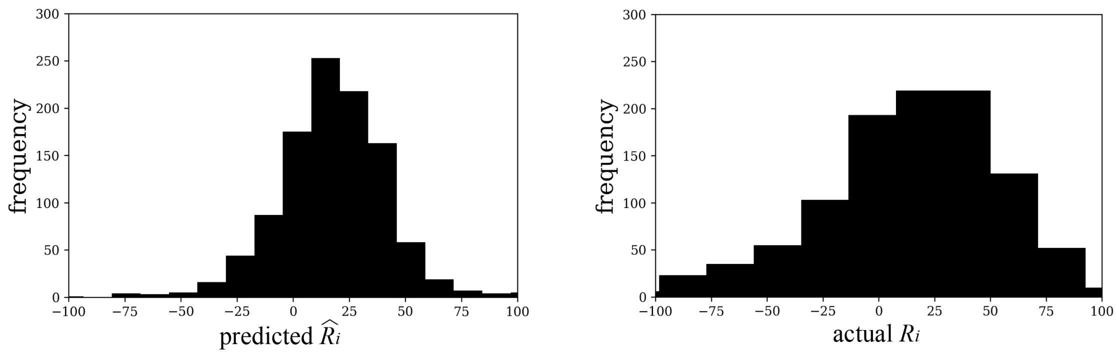



Fig. 4.4 Distribution of the model result (left: $\widehat{R}_i$, right: $R_i$)

The predicted distribution of $\widehat{R}_i$ is then utilised for classifying winners and losers. That is, the classification model identifies the winners ($\widehat{S}_{k,i} = 1$) and losers ($\widehat{S}_{k,i} = 0$) for a given threshold $k$. Table 4.5 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 $\widehat{R}_i$ shown in Figure 4.4 provides information to decide the optimal $k$ by calculating the number of $\widehat{S}_{k,i} = 1$, i.e., prospective winners.

| $k$% | -30 | -20 | -10 | 10 | 20 | 30 |
|---|---|---|---|---|---|---|
| MCC values | 0.17 | 0.14 | 0.16 | 0.36 | 0.38 | 0.29 |

Table 4.5 MCC result with different threshold value $k$

Table 4.6 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 ($\widehat{R}_i > 20\%$) 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 4.6, 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 effectiveness of the TOU programme by 25.5%[6], and identify the majority of potential winners (84.9%) before a tariff is implemented.

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

Table 4.6 Confusion matrix for $k$ =20

### 4.6.2 Feature Importance

Table 4.7 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 $\widehat{R}_i$ prediction (Breiman [29]). 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 [208]), demographic characteristics are reflected in the historical load profiles, suggesting that these static features are not so important.

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

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

Table 4.7 Feature importance

### 4.6.3 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 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.

This result can be aligned with previous research on the effectiveness of gamification as discussed in Section 4.3.2. Specifically, it is implied 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. Although the causality link between households' online engagement and their peak reduction should be further investigated, this implication can provide an additional opportunity for energy companies to optimise TOU planning; they often believe financial incentives (similar to tariff incentive in Section 4.4.1) 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.

## 4.7 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 work 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 work can be summarised as follows. First, the predictive model performs better for the identifying winner rather than identifying losers. The highest model accuracy 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 chapter 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 author believes that a scarcity of public datasets has prevented researchers from developing models and testing external validity. This chapter 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 Chapter 3 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.

# Chapter 5

# Data Driven Model for Rooftop Excess Electricity Generation

## Highlights

- A forecasting problem for excess generation from residential PV systems is similar to load forecasting problem under a TOU tariff in Chapter 3 and 4.
- A data-driven Gaussian Process model is chosen to address the stochastic nature of excess generation.
- A drawback of the decoupled approach for excess generation is examined.
- A year long dataset from 287 households in Tokyo Japan, is used to derive the forecasting model.
- Results show that a-year-long data from 18 households is sufficient for accurate prediction of excess generation across a uniform geographic and socio-economic setting.

## Collaborators

- Yeonsook Heo[1] contributed to the discussion on the modelling of Gaussian Process.

The final analysis chapter addresses the "excess generation forecasting problem", defined in the Chapter 2. This chapter briefly overviews the current circumstances of rooftop solar

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installations and related subsidies, and more detailed examination in existing approaches to forecast the residential excess generation from rooftop solar panels before presenting modelling works.

## 5.1 Introduction

Residential PV systems make up the dominant share of solar energy deployment worldwide, and they are anticipated to remain the dominant driver for PV generation deployment: around 60% in 2010, and 40% in 2050 among the four market segments (residential, commercial, utility-scale, and off-grid) (Figure 5.1) (IEA [136]).

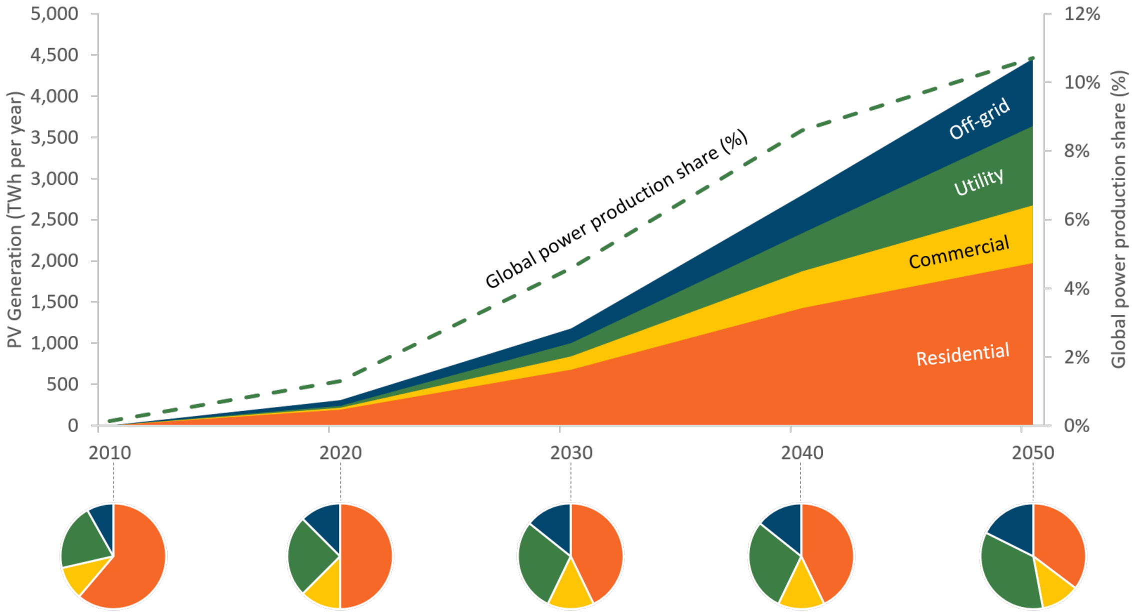


Fig. 5.1 Evolution of PV electricity generation by end-use sector (IEA [136])

In the residential sector, there is usually a poor correlation between load and generation; more energy is generated during daytime, whilst consumption is highest in the morning and in the evening hours (see Figure 5.2. Excess generation is the result of this mismatch between the timing of generation and consumption. Energy traders participating in liberalised markets aggregate the excess energy produced by many rooftop installations to sell it. They need to notify the amount of energy that they can provide in advance and in case of imbalance between the bid and the actual amount of energy they are subject to penalties and/or loss of revenues (Pinson et al. [219]). In this scenario, accurate excess generation forecasting becomes crucial to optimise the revenues of the traders, and thus encourage the installation of rooftop PV systems.

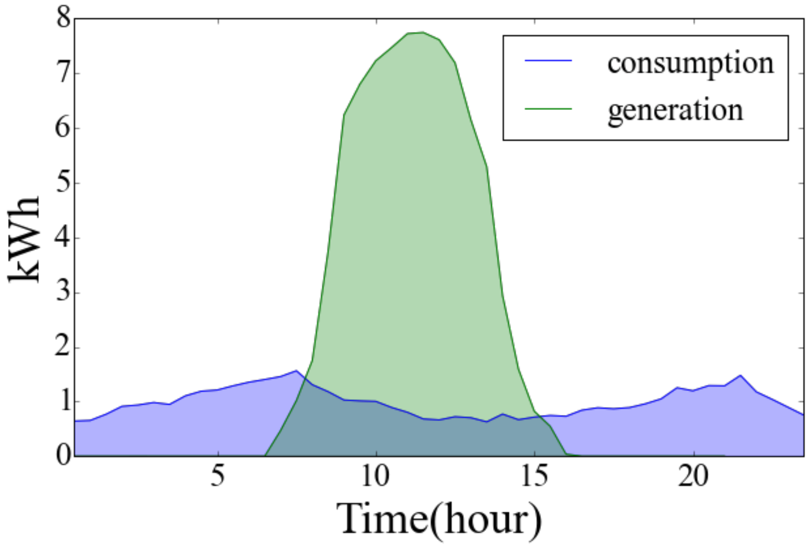


Fig. 5.2 Typical daily energy usage of a PV installed household. excess generation is a result of a mismatch between the timing of PV generation and consumption)

Accurate prediction of excess generation is also essential for grid operators, since inaccurate predictions of excess electricity into the grid from several thousands of PV systems, scattered geographically, can be challenging for grid stability (Denholm and Margolis [60]).

PV generation, on-site consumption, and therefore, excess generation is measurable in real-time through a single device – the smart meter. Indeed, many countries are showing a strong commitment to support large-scale smart-metering programs, with the aim of better real-time management of electricity flows through the grid. In 2009, the European Commission Directive required that 80% of EU households have smart meters installed by 2020. This is likely to result in an exponentially increasing available datasets, which will be invaluable for predicting future excess generation using data-driven methods.

Excess generation is essentially the result of the difference between real-time PV generation and on-site load consumption. Individual models for predicting PV generation and on-site consumption have been researched extensively. However, to the author's knowledge, no model exists that integrated generation and consumption uniquely for the goal of quantifying excess generation. This chapter compares the forecasting accuracy of an integrated excess generation model against the more traditional decoupled approach and thereby examines the necessity of an integrated excess generation model. Furthermore, various financial programmes which incentivise households to maximise (or minimise) the excess generation, make this problem even more complicated. Although this is not strictly a time-of-use tariff itself as discussed in previous chapters, these programmes effectively function like a time-of-use tariff in that they encourage demand adaptation to maximise the financial incentives given by a subsidy. Therefore, the final analysis in this thesis is to address the "excess generation forecasting problem".

Next section examines the financial incentive/dis-incentive for the excess generation. The third section provides an overview of relevant existing energy demand and PV generation models. The following section describes the dataset of an illustrative study and proposes an integrated modelling procedure for predicting excess generation. Finally, prediction results of the proposed model are compared against decoupled model (model for PV generation minus load consumption). The conclusion explains two key findings and scheduled future work.

## 5.2 Financial Support for Excess Generation

Various government programmes promote a range of small-scale renewable and low-carbon electricity-generation technologies. Until renewable power reaches grid parity, subsidisation schemes are necessary in order to accelerate renewable power generation. Two notable schemes are explained below.

***Feed-In-Tariffs***

Feed-in tariffs (FIT) are the most extensively-used policy programmes for accelerating renewable energy deployment all over the world. FIT account for a greater share of renewable energy development than either tax incentives or renewable portfolio standard (RPS) policies. Feed-in-tariff programs exist in 75 countries, states, and provinces around the world; altogether, FIT are responsible for approximately 75% of global PV development (Cory et al. [51]).

In a FIT program, electricity from a grid-connected rooftop photovoltaic power station can be sold to the grid at a higher price than the grid charges to the consumers. This arrangement provides a secure return for the installer's investment. However, the minutiae of the financial mechanism shows discrepancy depending on a country, as illustrated by the two examples in section 5.2.

***Net metering***

Net metering is another prevailing scheme designed to foster private investment in renewable energy. Even though specific design details vary, net metering allows customers with PV systems to reduce their electric bills by offsetting their consumption with PV generation. In effect, net metering sells PV-generated power to the utility at the customer's marginal retail electricity rate.

### Incentive and Disincentive for Excess Generation

Some countries encourage on-site consumption of on-site generation, and others do not. This divergence in philosophy is epitomised by the types of subsidisation incentives offered to residential PV owners. This financial scheme influences energy-usage behaviour of household occupants, and makes it arduous to model globally standardised excess generation models, unlike the PV generation model, which basically follows the laws of thermodynamics.

Two countries using opposite incentive poles—the UK and Japan—are illustrated below.

***Case 1: A disincentive for excess generation: UK***

In the UK, consumers have a stronger incentive to utilise the preponderance of their generated electricity on sunny days, thereby minimising excess generation. As seen in Table 5.1, UK customers receive a guaranteed FIT for all generation (10-14 p/kWh), plus an 'export tariff' (4.77 p/kWh) for excess generation (Ofgem [202]). According to uSwitch, a UK energy-price comparison service and switching website, the FIT is much smaller than the average electricity bill (12-15 p/kWh) (Uswitch [274]). Therefore, customers have incentive to consume their generated electricity, rather than export it to the grid.

This is, however, theoretical. Up to now, Ofgem assumes that excess electricity exported to the grid is 50% of total generation for PV systems with total installed capacity of 30kW or less, where it is not possible or practical to measure electricity generation with an export meter (Ofgem [201]).

This situation will change with the emergence of smart meters, which will allow the provision of more tailored incentives based on metered excess generation. The UK Government is obliging energy companies to install smart meters for their customers by 2020 (DECC [59]). With smart meters, export tariff will be paid according to the metered excess generation, rather than a fixed ratio.

***Case study 2: an incentive for excess generation: Japan***

In Japan, FIT is only paid for excess generation— not total generation, as in the UK. FIT prices are currently much higher (38-42 JPY per kWh) than the average electricity bill (20-25 JPY per kWh) (METI [185]). Customers have a strong financial incentive to maximise their excess generation, and so are willing to change their consumption behaviour by shifting electricity-heavy appliances, such as dishwashers and washing machines, to evening, rather than wasting opportunities to export excess generation with subsidised prices. By shifting electricity usage from daytime to night-time, a household saves roughly 15-20 JPY/kWh.

In this work, we will work with a dataset in Japan, therefore the customer has an incentive for excess generation.

Table 5.1 FIT schemes in the UK and Japan

| | UK | JAPAN |
|---|---|---|
| **Generation Tariff** | 10-14 p/kWh | - |
| **Export Tariff** | 4.77 p/kWh | 38-42 JPY /kWh |
| **Average Electricity Bill** | 12-15 p/kWh | 20-25 JPY /kWh |

## 5.3 Literature Review

Excess generation can be considered as a function of PV generation and on-site load consumption. PV generation and residential consumption models are useful in pre-screening important features for excess generation modelling as explanatory variables/inputs. In this section, recent studies in these fields are reviewed in order to identify key variables for excess generation modelling.

### 5.3.1 PV Generation Models

Models for predicting PV generation are categorised into engineering (physical) models and statistical time-series models. An engineering model involves a physics-based model of PV panels, which converts solar irradiance to output power. Various simulation tools are currently available to perform PV simulation, e.g., TRNSYS; RETScreen; PVSIM; PVFORM; PVNet; and so on. The RETScreen Photovoltaic Project Model (Centre [40]) mainly utilises site-specific weather information (especially insolation), as well as configuration of a PV system. TRNSYS is used for dynamic simulation with modelling of solar radiation, PV array output, and inverter output (Mondol et al. [191]).

On the other hand, statistical models predict future PV output by computing the trend of the output based on present and past samples of PV generation. Meteorological parameters, including temperature, clearness, dust, and relative humidity, are frequently considered as explanatory variables in such models (Toğrul and Onat [266]). For example, (Long et al. [170]) survey multiple features (as inputs) that can improve accuracy of daily PV generation based on two years' data collected in Macau on four types of machine learning models: Artificial Neural Network, Support Vector Machine, k-nearest neighbour, and the multivariate linear regression. Parameters shown to be important across all the four models include maximum air temperature, daily mean air temperature, insolation, wind-speed, precipitation, and day-before PV generation.

(Huang et al. [132]) contrasted the performance of an engineering (diode) model and a statistical model (Neural Network) in a case study of a 1 MW PV station. The performance difference is measured by nRMSE. The chapter finds that the statistical model using temperature, cloud coefficient, irradiance, humidity, and the position of sun as inputs shows better performance than a diode physical model.

### 5.3.2 On-site Load Models

Various technical studies for modelling residential sector energy consumption are relevant for identifying key features that influence household electricity consumption patterns during daytime hours (defined as the hours during which excess generation is possible).

One study (Parti and Parti [214]) identifies important features influencing consumption corresponding to end-use groups: the number of occupants, electricity price, household income, floor area, and heating/cooling per unit area.

(Shimoda et al. [247]) developed a residential end-use energy consumption model for the city of Osaka, Japan. In this model, households are rated based on the number of family members, appliance ownership levels, and appliance ratings. (Shimoda et al. [246]) simulated electricity consumption used by each appliance at five-minute intervals, according to the occupants' energy-usage activity. These studies yield valuable conclusions for end-use electricity consumption patterns. First, electricity consumption depends more on the number of family members in a household than on the total floor area of the house (unless electric space heating and cooling are dominant). Second, the influence of the total floor area on electricity consumption is stronger in a large family, since the number of occupied rooms and energy use for lighting, heating, and cooling increases with the number of family members. Finally, for the same floor area and household size, the electricity consumption in a detached house is greater than that of an apartment.

## 5.4 Modelling Procedure

### 5.4.1 Dataset

Thirteen months' (January 2014 – January 2015) data from a grid-connected PV system installed on the grid-connected rooftop of 287 detached residential dwelling located in the Tokyo area is considered. Figure 5.3 displays the weekly averaged energy dataset over all sampled households: excess generation and PV generation have peaked during the spring to summer (around week 15-32) except rainy season (week 20-25), whereas electricity consumption has dual peaks in the summer and winter. The dataset has been strictly anonymised. In addition to monitored energy data, some parameters found useful upon reviewing existing models are collected via questionnaires. These include panel characteristics (angle, azimuth and capacity), number of people living in a household, floor area (m2), and heating source (gas-heating/all electric). Some households are all-electric dwellings, using only electric power for heating and domestic hot water, cooking equipment, etc. This means the entire energy consumption of such dwellings is recorded using only the electricity monitors.

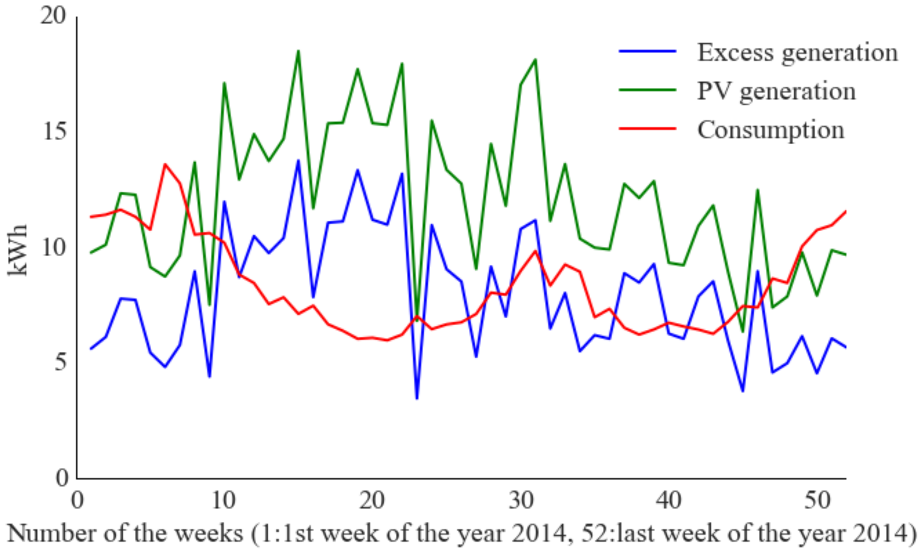


Fig. 5.3 Averaged weekly energy dataset of all households from 1st January to 31st December 2014

Metered energy dataset, PV generation, consumption, and excess generation, are aggregated over daytime (6am to 6pm) since only daytime energy activities should be considered for this purpose: $G_d$ (daytime PV generation), $C_d$ (daytime consumption), and $E_d$ (daytime excess generation). The list of available explanatory variables per household used in this analysis is shown in Table 5.2.

One important note is that near-time value of energy dataset by itself is not appropriate to utilise as an explanatory variable as it is unavailable for future prediction. However, aggregated value over a time-period T might be fair to add if T is long enough since these values are inferable from similar sites within the region, or from historical data. In this computation, period T is set as January 2014 to December 2014.

The dataset used in this study is classified into two types of data: the explanatory variables and the objective variable. The objective variable is always excess generation $E_d$ in this chapter, and the explanatory variables are described in Table 5.2. The importance of these variables will be investigated for model development.

Table 5.2 List of explanatory variables

| Variable | Description |
|---|---|
| $W_{house}$ | Sum of panel capacity in a house |
| $AZ_{house}$ | Largest panel's azimuth in a house |
| $AN_{house}$ | Largest panel's angle in a house |
| $C_{T,Mean}$ | Average of $C_T$ (Set of $C_d$ over the period $T$) |
| $DNR_T$ | Daytime/Night-time ratio over the period $T$ |
| $E_{T,Mean}$ | Mean of $E_d$ over the period $T$ |
| $E_{T,Max}$ | Max of $E_d$ over the period $T$ |
| $E_{T,STD}$ | Standard deviation of $E_d$ over the period $T$ |
| $E_{d\text{-}j}$ | Historical Excess generation before $j$ day ($j$ =1,2,3,7) |
| $E_{system}$ | Heating system (0: gas heating, 1: all electric) |
| $N_{people}$ | Number of people in a house: from 1 to 7 |
| $n_{day}$ | Number of day |
| $m$ | Month |
| $Week$ | Week |
| $La$ | Latitude |
| Lo | Longitude |
| $S_{floor}$ | Floor area |
| $t_{d,ave}$ | Average of daily air temperature (Celsius) |
| $t_{d,max}$ | Daily maximum temperature (Celsius) |
| $t_{d,min}$ | Daily minimum temperature (Celsius) |
| $h_d$ | Daily Humidity (Percentage) |
| $P_{rd}$ | Daily Precipitation (mm) |
| $v_d$ | Daily Wind velocity (m/s) |
| $I_d$ | Daily Insolation (kWh) |

To evaluate the performance of modelling, this dataset is split into two groups: a training dataset and an evaluating dataset. The datasets are grouped by each month for monthly comparison as shown in equation 5.1:

$$\mathbf{D}_m = \{\{\mathbf{x}_m, \mathbf{y}_m\} \mid m = 1, 2, \cdots 13\} \tag{5.1}$$

where, $m$ is the month of dataset starting from January 2014, and m=13 is the January 2015.

### 5.4.2 Model Selection

In order to quantify uncertainty in excess generation predictions, this work uses a Gaussian Process (GP) model (Williams and Rasmussen [294]) for an excess generation modelling framework. Traditional linear regression models are easier to implement but pose two major drawbacks: First, they assume (linear) relationship between independent and dependent variables. As a result, they do not capture complex nonlinear behaviour of excess generation and multivariable interactions among variables. Second, they assume constant variance of predictions throughout the entire range of observations, which implicitly requires large data sets to ensure the prediction reliability. Unlike the traditional linear models, a GP model does not require specification of the structural relationship between independent and dependent variables, and consequently they can capture complex behaviour with fewer parameters. In addition, as the parameters of the GP model are trained under a Bayesian setting, the resulting model naturally allows quantification of uncertainties in prediction. (Heo and Zavala [121]) demonstrated the strengths of the GP model to predict energy use in comparison to the linear model.

GP is a collection of random variables, any finite number of which has Gaussian distributions (Williams and Rasmussen [294]). GP is specified by a mean function m(x) and covariance function $k(x_i, x_j)$. A mean function is a matrix of mean output values for the given set of input values. Typically, the mean function m(x) is assumed to be zero. The covariance function $k(x_i, x_j)$ used in this analysis is defined in Equation 5.2. The covariance matrix quantifies proximity between two sets of input values with respect to their outputs. We used a squared exponential function, which is appropriate for modelling very smooth functions.

$$k\left(\mathbf{x}_i, \mathbf{x}_j\right) = \theta_0 \exp\left\{-\frac{1}{2\gamma^2}\left\|\mathbf{x}_i - \mathbf{x}_j\right\|^2\right\} + \theta_1 \tag{5.2}$$

where $\theta = (\theta_0, \theta_1, \gamma)$ are hyper parameters, each of which denotes signal variance factor, noise variance factor, and length scale factor, respectively. Those hyper-parameter values are trained to maximise the fit between predictions and observations through a log likelihood function of $\log P(\mathbf{y} \mid \theta)$ given by:

$$\log P(\mathbf{y} \mid \theta) = -\frac{1}{2}\left\{\log\left(\mathbf{K}(\mathbf{X},\mathbf{X}) - \mathbf{y}^T\mathbf{K}(\mathbf{X},\mathbf{X})^{-1}\,\mathbf{y} - n\log(2\pi)\right\}\right. \tag{5.3}$$

where y denotes observations on the output (excess generation in our study) at known conditions x (e.g., all the explanatory variables in Table 5.2) and K is covariance matrix for given set of input values X. With the optimal hyper parameters $\theta^*$ derived from training, the mean vector $\mu_{\text{pred}}$ and the covariance matrix $V_{\text{pred}}$ to yield probabilistic outputs for new input values $X^*$ are given by equations 5.4 and 5.5:

$$\mu_{\text{pred}} = \mathbf{K}\left(\mathbf{X}^*,\mathbf{X}\right)^{\mathrm{T}}\mathbf{K}(\mathbf{X},\mathbf{X})^{-1}\mathbf{y} \tag{5.4}$$

$$\mathbf{V}_{\text{pred}} = \mathbf{K}\left(\mathbf{X}^*,\mathbf{X}^*\right) - \mathbf{K}\left(\mathbf{X}^*,\mathbf{X}\right)^{\mathrm{T}}\mathbf{K}(\mathbf{X},\mathbf{X})^{-1}\mathbf{K}\left(\mathbf{X},\mathbf{X}^*\right) \tag{5.5}$$

For model validation, the dataset is randomly split into two subsets based on a commonly considered rule: 70% for training and 30% for test. With the test dataset, we compare predictions with actual observations with use of MSE (mean squared error) defined in Equation 5.6.

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}\left(\mathrm{y}^*(i) - \mu_{\text{pred}}(i)\right)^2}{n} \tag{5.6}$$

where $y^*$ is the metered excess generation, $\theta_{\text{pred}}$ is the predicted excess generation, and n is the number of data in the test dataset.

### 5.4.3 Feature Selection

Correlation analyses are performed to identify relative importance of PV generation and on-site consumption on excess generation. All data points in 2014 are used. The Pearson correlation values are 0.93 with PV generation, and -0.29 with consumption. These results show that PV generation has a strong correlation while on-site consumption has a weak correlation, and it is visible in Figure 5.3.

We identified twenty-seven potential explanatory variables for model development (Table 5.2), which can be grouped into eight feature clusters (FC) in order of sampling cost (Table 5.3); accordingly, static features (FC 1-4) come first, followed by time-varying features such as meteorological information (FC 5) and historical energy consumption/generation (FC 6-8). Consumption related parameters, average daytime consumption and daytime/night-time ratio

Table 5.3 List of feature clusters (FC)

| Cluster | Description | Features |
|---|---|---|
| FC 1 | Panel attribute (static) | $W_{house}$ $AZ_{house}$ $AN_{house}$ $Cell_{house}$ |
| FC 2 | Household characteristic (static) | $N_{people}$ $S_{floor}$ $E_{system}$ |
| FC 3 | Geospatial information | La Lo |
| FC 4 | Time information | $m$ $Week$ $n_{day}$ |
| FC 5 | Meteorological information | $t_{d,ave}$ $t_{d,max}$ $t_{d,min}$ $h_d$ $Pr_d$ $v_d$ $I_d$ |
| FC 6 | Consumption indicators | $DNR_T$ $C_{T,Mean}$ |
| FC 7 | Excess generation aggregation | $E_{T,Max}$ $E_{T,Mean}$ $E_{T,STD}$ |
| FC 8 | Historical dataset | $E_{d\text{-}1}$ $E_{d\text{-}2}$ $E_{d\text{-}3}$ $E_{d\text{-}7}$ |

over time T, are grouped within FC 6. Aggregated values of historical excess generation over time T are grouped within FC 7. FC 8 includes near-time excess generation; for example, $E_{\text{d-1}}$ is previous day's excess generation.

### 5.4.4 Model Development

In a model development, identifying an optimum set of key features is vital to ensure forecasting accuracy while minimising the cost of data collection. Required computation power is also greatly reduced as the number of explanatory variables becomes smaller. This section describes the process followed in this project to identify an optimum set of explanatory (input) variables for the GP model.

First, individual feature effect on the model accuracy is examined by adding one parameter at a time. As solar insolation is well-acknowledged as an important parameter that determines PV generation and consequently excess generation, solar insolation $I_d$ is selected as the primary feature, and all other features listed in Table 5.3 are subsequently added one at a time. Figure 5.4 plots the relative influence of all features in order of MSE.

Overall, most features within the same cluster shows similar effect on prediction accuracy, as it is visualised in different colours in Figure 5.4. Aggregated historical excess generation features under FC 7 are the top three (MSE value of 10), followed by panel capacity ($W_{\text{house}}$) and the four FC 8 features. The lowest MSE value was achieved by insolation $I_d$ and historical value of maximum daily excess generation over the period T: $E_{\text{T,Max}}$.

As the second step, all features are added incrementally in order of their corresponding MSE values to determine the optimal number of key explanatory variables to be included in the model. In this sequential analysis process, only features that achieved more than 1% of MSE improvement are considered. As the outcome of this sequential process, $I_{\text{d}}$, $E_{\text{d-1}}$, $E_{\text{T,Max}}$, $t_{\text{d,min}}$ are the four features that best explain excess generation. This experiment clearly shows

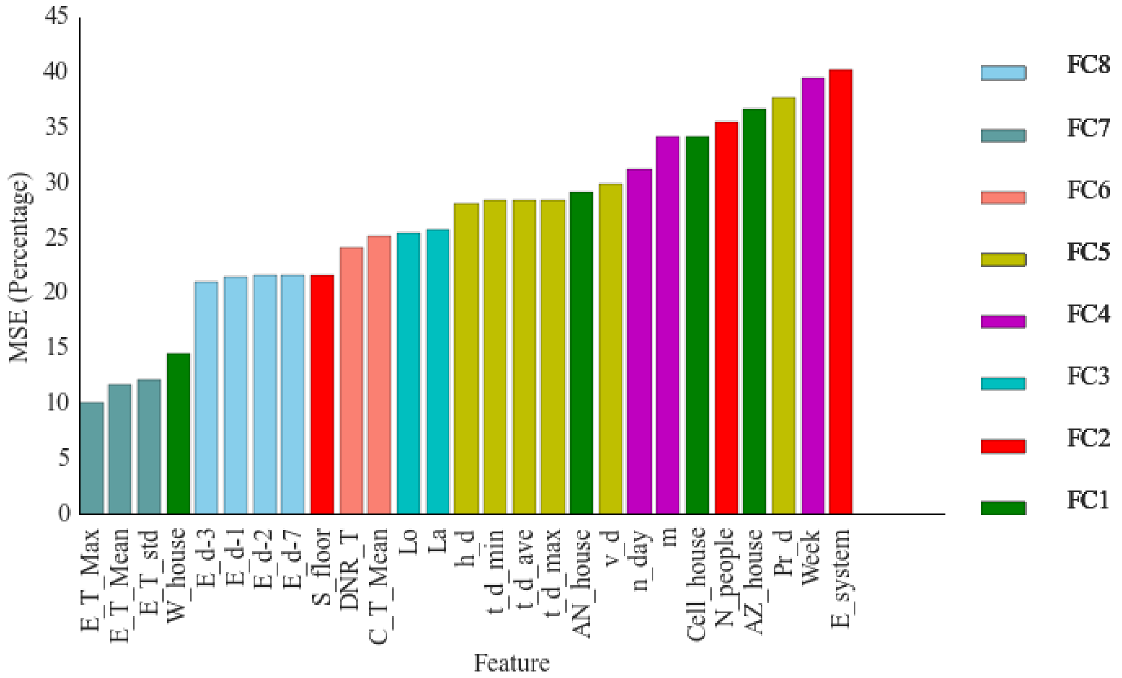


Fig. 5.4 Model accuracy trained with a single variable and sorted in order of MSE score (colour represents FC)

Table 5.4 Result comparison of the model

| **Input Features** | **MSE** |
|---|---|
| $I_d$ $E_{d\text{-}1}$ $E_{T,Mean}$ $t_{d,min}$ | 9.032 |
| All 28 features | 8.212 |

the importance of analysing model features collectively, as it enables removing important but redundant variables. For the modelling purpose, static parameters such as number of occupants do not explain excess generation.

Finally, the accuracy of the model with these four features is examined by comparing the prediction accuracy of the model with the four features only against a model with all the features as input variables. Table 5.4 shows that the model with the top four features produces a competitive level of accuracy in comparison to using all the features as input variables.

### 5.4.5 Model Validation

The developed model is validated against unseen evaluation dataset $D_{\text{eval}}$. From the entire dataset, $D_{\text{train}}$ is a training dataset starting from January 2014 to m-1 month, while $D_{\text{eval}}$

is the evaluation dataset starting from month m, as defined in Equations 5.7 and 5.8. As an increase of m, the model trained with longer training period is expected to have better extrapolation for an unseen evaluation dataset.

$$\mathbf{D}_{\text{train}} = \left\{ \sum_{N=1}^{m-1} \mathbf{D}_m \mid m = 2, 3, \cdots 13 \right\} \tag{5.7}$$

$$\mathbf{D}_{\text{eval}} = \left\{ \sum_{N=m}^{13} \mathbf{D}_m \mid m = 2, 3, \cdots 13 \right\} \tag{5.8}$$

### 5.4.6 Decoupled Model Description

As described in the introduction, excess generation can be decoupled into two energy components: PV generation and on-site consumption. Hence, it is natural to think that two individual energy models can substitute an integrated excess generation model. In theory, the exact daily aggregated value of excess PV generation can be expressed as:

$$E_d^{\text{integrated}} = \sum_{\text{day}} \max(g(t) - c(t), 0) \tag{5.9}$$

where g(t) and c(t) are respectively the generation and consumption at time t.

When we approximate excess PV generation by separately aggregating daily consumption and generation, we however end up estimating excess generation as:

$$E_d^{\text{decoupled}} = \max\left(G_d - C_d, 0\right) \tag{5.10}$$

where $G_d = \sum_{day} g(t)$ and $C_d = \sum_{day} c(t)$

We notice that $E_d^{\text{integrated}} \geq E_d^{\text{decoupled}}$ if g(t) is smaller than c(t) any time: hourly electricity demand is higher than hourly on-site generation. If no aggregation over a daily time duration is performed, the decoupled approach can properly predict hourly excess generation.

However, if consumption and generation values are aggregated over any duration, the decoupled approach is most likely to underestimate the true value of excess generation by subtracting some electricity demands, met by the grid supply, from the aggregated on-site generation.

Figure 5.5 represents the distribution of the discrepancy between the integrated and decoupled approaches ($E_d^{\text{integrated}}$ - $E_d^{\text{decoupled}}$). This figure confirms the concerned discrepancy happens frequently causing more than 2kWh differences. This illustrates the unavoidable nature of underestimation in the decoupled approach: excess generation is highly likely larger than the value obtained from a decoupled approach if the values are aggregated over any duration.

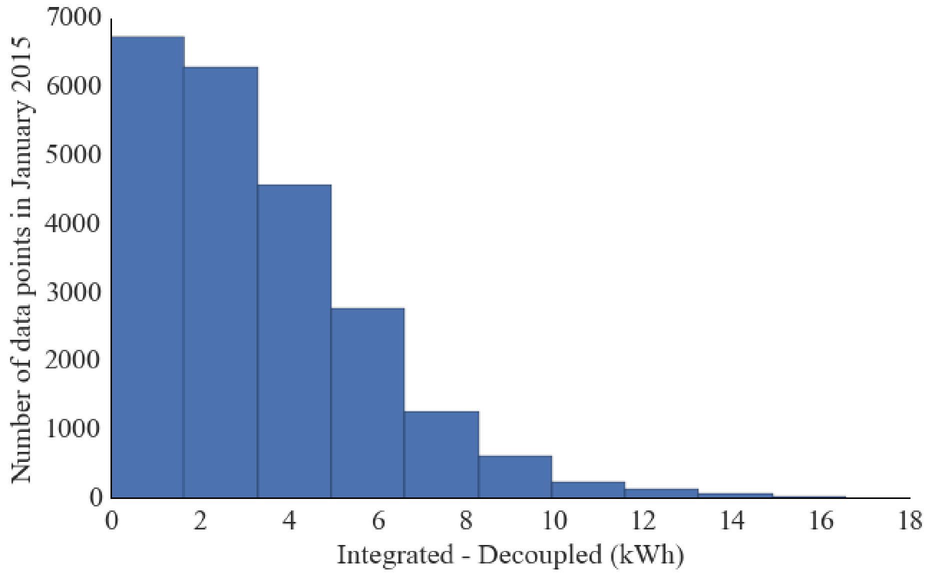


Fig. 5.5 Error distribution of ($E_d^{\text{integrated}}$ - $E_d^{\text{decoupled}}$) in January 2015

### 5.4.7 Prediction Results

Prediction results by the proposed integrated excess generation models are compared against both metered data and the values obtained from the decoupled approach. In the decoupled model, metered daytime (6:00 to 18:00) aggregated values of PV generation and consumption are used, instead of modelling them individually. This means that the values used removes inaccuracy of these models and uncertainties of model parameters, and represents the most accurate values.

Figure 5.6 displays the excess generation predicted by the integrated excess generation model and the decoupled model against true values of excess generation (metered data). This shows that the decoupled approach tends to consistently underestimate the exact value of excess generation, and this phenomenon is remarkable during the winter seasons. This result confirms the previous mathematical examination on the drawback of the decoupled approach, and, therefore, elucidates the necessity of development of tailored excess generation modelling.

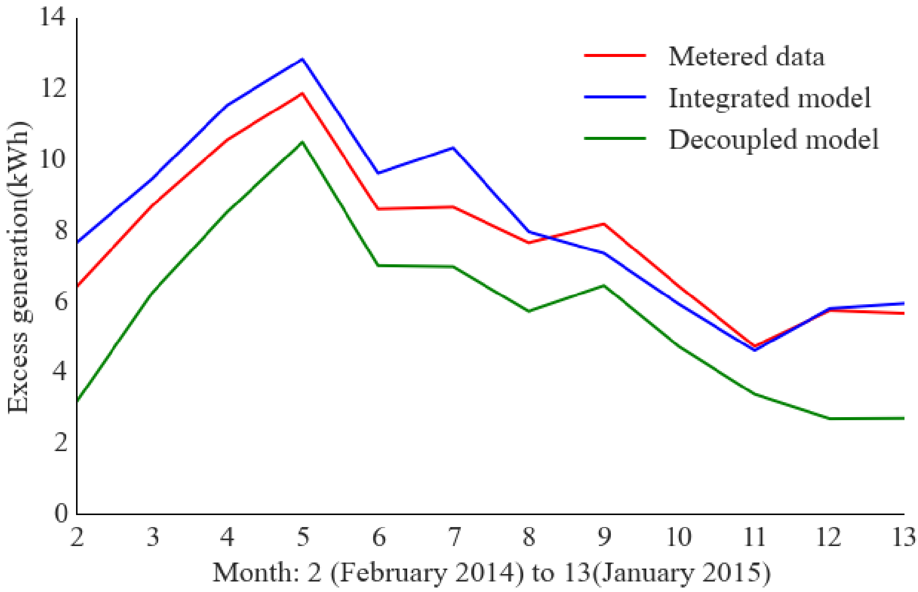


Fig. 5.6 Monthly scale of forecasting results against metered data from January 2014 to January 2015

### 5.4.8 Length of the Training Period

As shown in Figure 5.6, the integrated excess generation model tends to overestimate in peak generation periods during spring and summer seasons, and prediction error is noticeably low during the autumn and winter seasons. Whether the model adjusts its tendency of overestimation to slight underestimation by learning from more datasets, or the model itself has a tendency to overestimate in peak generation, and underestimate in off-peak generation, is yet to be analysed.

For further examination, the forecasting results are illustrated at daily resolution. Figure 5.7 and Figure 5.8 displays two distinctive months. These figures confirm that the model successfully followed the fluctuation of excess generation closely on daily basis. In Figure 5.7, the prediction is constantly overestimated, whilst in Figure 5.8, the tendency is adjusted mostly. This leads to a conclusion that the model modified its initial overestimation tendency, by learning from different seasonal dataset. Hence, this work reconfirms the importance of a-year-long minimum data collection in a single site, with multiple distinct seasons.

### 5.4.9 Effect of the Number of Training Points

The biggest barrier for the development of such a data-driven model is the cost incurred in collecting actual energy data from residential households for a-year-long period. The time complexity is also a factor; a GP has cubic time ($n^3$), where n is the number of training data

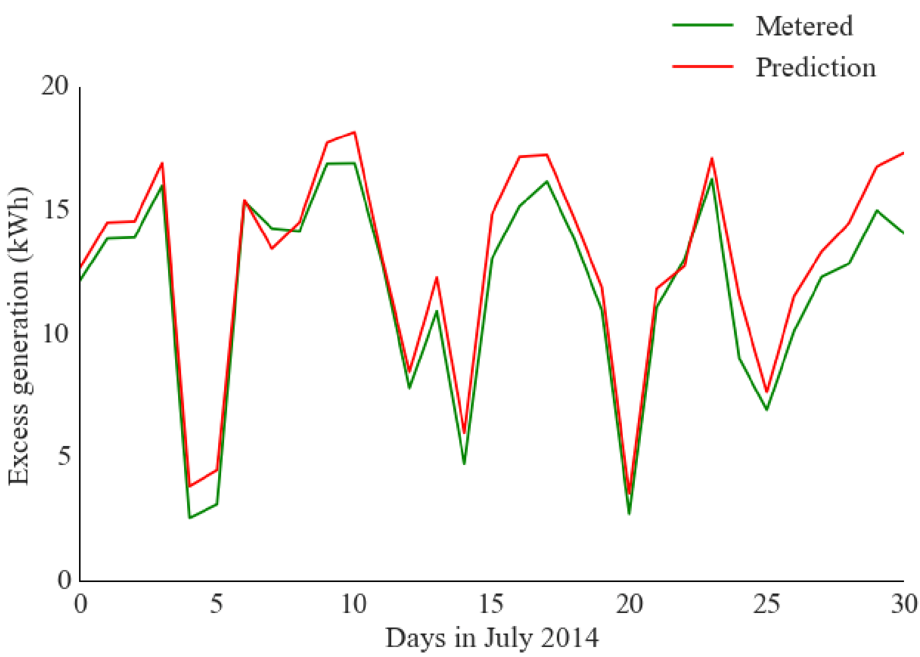


Fig. 5.7 Daily scale of forecasting results against metered data in July 2014 (overestimated example)

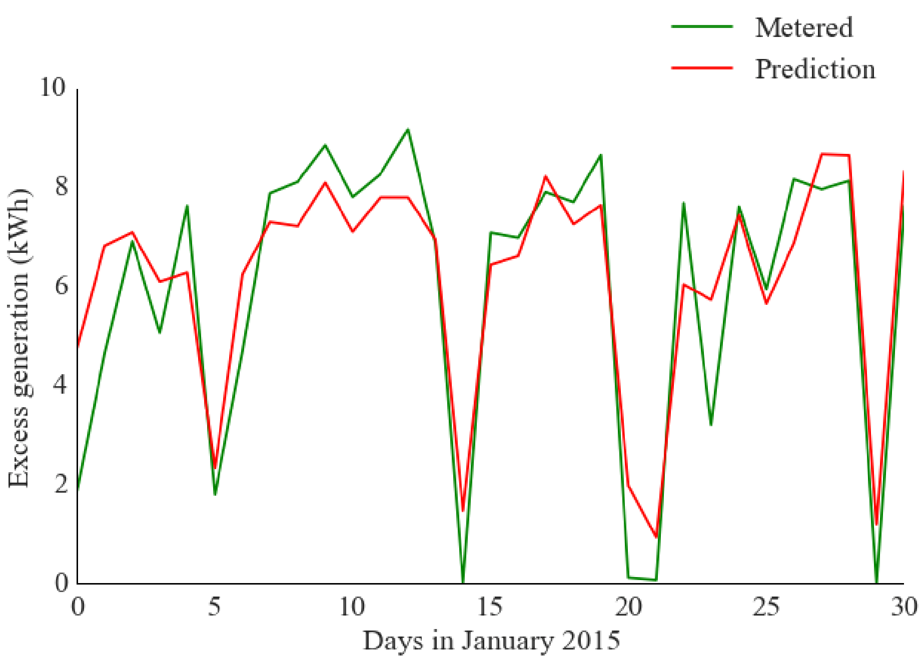


Fig. 5.8 Daily scale of forecasting results against metered data in January 2015 (underestimated example)

points. Hence, minimising the size of the training dataset has vital importance for realistic implementation. In this section, the consequence of the number of training points on the performance of the model is analysed. To do so, we consider limited data points randomly chosen from all data points and the result is plotted in Figure 5.9.

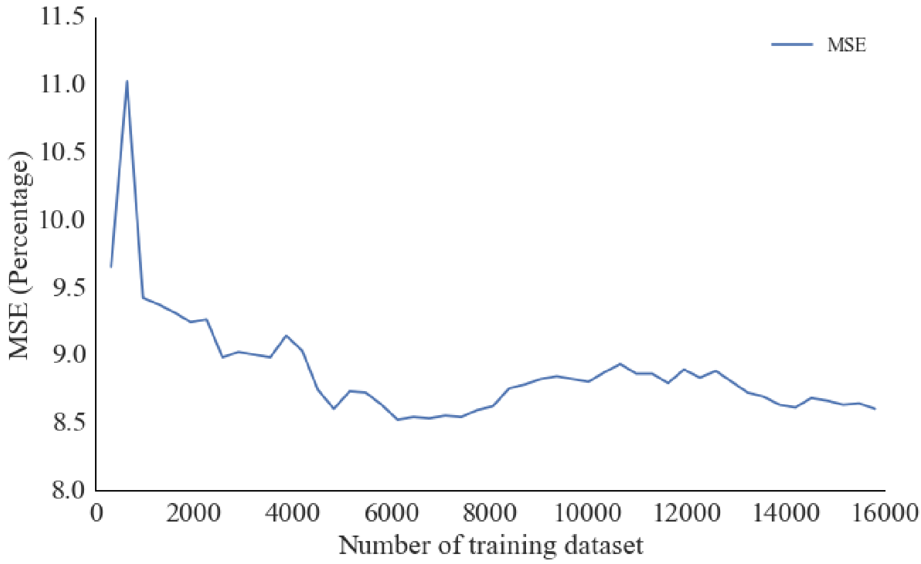


Fig. 5.9 Effect of the number of data point on the model accuracy. Each data point represents a day of a household.

In the range of 6,000-16,000 points, the MSE changes are always within the same order of magnitude. If the number of data points is reduced below 6,000, the MSE increases significantly. The outcomes indicate the model seems to converge by 6,000 data points. This trial points out that 6,000 data points is the optimal amount of training data necessary to accomplish the best performance with the least computation cost. If 365 data points can be collected per a household for a-year long survey, 6,000 data points is equivalent to 18 households. This number sounds realistic to reproduce this trial anywhere in the world.

## 5.5 Conclusion

To the best of the author's knowledge, this chapter proposed the first integrated data-driven GP model for daily excess electricity generation. The analysis presents a framework to develop a GP model by identifying effective features, and demonstrates a way to minimise the number of necessary datasets without compromising predictive accuracy.

This chapter demonstrates how to optimise required set of features, training data periods and number of households, which directly link to cost of data collection and computational power. Four features, two of historical excess generation data and two of weather parameters, are shown to be effective combination. Also, a-year long data collection from 18 households produces the optimal number of training datasets for robustness against seasonality.

This research also reveals a particular drawback of the decoupled approach to quantify excess generation. The proposed model presents much higher prediction performance than the decoupled value (daytime generation minus daytime consumption), which has unavoidable tendency of significant underestimation. It reaffirms the necessity of excess generation model.

# Chapter 6

# Conclusion and Future Work

## 6.1 Conclusion

The primary objective of this thesis was to examine the opportunities and challenges associated with time-of-use (TOU) tariffs at the national level, using smart meter data. As one core factor of the vision of Energy 3D, the digitalisation is of paramount importance in the energy sector. This paradigm has been introduced by utilising "Smart Technologies" such as smart meters that can connect local energy systems to the information network. In response, the demand for the analysis of the collected electricity consumption data via smart meters is soaring and there is a number of previous research existing such as load forecasting, load clustering, and demand response estimation in electricity pricing. However, as outlined in Chapter 2, these works leave several points untouched, which prevents utility companies from practically implementing the technologies at a large scale. As of today, although the penetration of the smart meter has reached high level in many developed countries, actual use a TOU tariff is still limited. Throughout the reviewing of the previous works in related field, this research work has found out four significant research gaps that need to be addressed in order to expand commercial applications of TOU tariffs.

Firstly, a practical framework to *forecast* users' load adaptation through a top-down approach has not been fully developed. This load forecasting capability is important for utilities to design a TOU tariff and estimate subsequent impacts in their load management. We name this as "TOU load forecasting problem". Existing modelling frameworks generally follow one of the three distinct approaches: econometric models with an emphasis on estimating price-elasticity, bottom-up disaggregation of household consumption according to electrical appliance usage, and top-down statistical models. The emergence of historical smart meter data makes the top-down statistical approach popular in industrial use. However, the reliance on historical data can have a number of drawbacks given that there is no in-built capability to model discontinuous user behaviour such as weather changes, introduction of new appliances, and the subsequent adoption to a TOU tariff. Therefore applying a top-down approach for a problem of forecasting consumer response to TOU tariffs is a challenging issue. Chapter 3 discusses this problem and proposes a top-down statistical medium-term load forecasting model for domestic demand response following the introduction of a TOU tariff. The chapter also discusses the accuracy of the model and the significance of its features, implying that statistical moments in the load profile are useful features.

Secondly, although time-of-use tariffs have the potential to be mutually beneficial - realising a cost reduction for both energy companies and customers if the customer responds to the price signalling - at the individual level such tariffs are likely to create both positive and negative financial outcomes because of customer characteristics and the potential capacity for peak shifting ("TOU winner detection problem"). Identifying the potential reducers or non-reducers before applying a time-of-use tariff can optimise the programme's design and marketing strategy, which can maximise the outcome of a TOU programme. Chapter 4 solves this issue, presenting a statistical model for determining the characteristics of so-called winners and losers, or households that will gain or lose from a TOU tariff plan, based solely on ex ante details.

Thirdly, availability of historical consumption dataset, including customer behavioural changes due to a TOU tariff intervention, is very limited. Given the importance of such dataset in utilising data-driven approaches, newly collected dataset is introduced in this thesis to address the "TOU public dataset problem". Chapter 4 also addresses this (described in detail in Appendix A) by publishing a new public dataset (CAMSL) of 1423 households in Tokyo, Japan, which includes historical smart meter data, household characteristics, and online activity variables collected over the course of two years of comprehensive TOU intervention in 2017 and 2018.

Finally, "excess generation forecasting problem" is introduced to show how similar incentivised programmes for a customer who has installed rooftop solar generation under various financial schemes, can leverage smart meter data. Excess generation is the unused generation from the rooftop solar panels exported to the electricity grid, and this amount has became substantial for demand management as the cumulative installed capacity of residential PV systems is growing in many countries. This problem can be considered as a "TOU tariff problem as well, therefore similar modelling framework has been applied for this problem. Chapter 5 introduces a data-driven Gaussian Process model for forecasting electricity excess production. The forecasting model is developed using an illustrative analysis that uses a year-long data from 287 households in Tokyo, Japan. The results indicate that a year's worth of data from 18 households is adequate to forecast excess generation accurately in a standardised geographic and socioeconomic context.

By bridging these gaps, this thesis aims to establish a foundation for helping utility companies conduct practical analysis of smart meter data, and encouraging the larger scale implementation of a "TOU tariff. The subsequent chapters summarise each chapters.

### 6.1.1 Intra-day Load Profiles under TOU Tariffs

The introduction of smart meters that allow the measurement of electricity load on a half-hourly basis creates an exciting demand-side management opportunity that is likely to benefit both utilities and consumers. TOU incentives are generally regarded as the most viable option for residential energy consumption optimisation. Being based on wholesale energy rates, TOU will allow consumers to plan their energy use to take advantage of price fluctuations. In a TOU tariff plan, certain price rates are set in advance and applied to various predefined periods of a calendar day, where the energy prices are separated by trends and rates.

Despite the fact that there is a substantial amount of research on demand response in energy pricing, a realistic framework for *forecasting* consumer adaptation under various TOU pricing plans has yet to be established. This research effort is devoted to this path in order to investigate potential solutions. The novelty of this study is that it is the first to provide top-down statistical modelling of domestic consumer demand response following the implementation of a TOU tariff, as well as to report on the accuracy of the model and significance of its feature. Statistical moments could be used to capture lifestyle-related constraints of each household, allowing this model to be agnostic to household characteristics. The proposed model was validated using data from 646 homes in Ireland before and after the implementation of the TOU Tariff. The Mean Absolute Percentage Error in forecasting average load for a group of homes using the Random Forest method is 2.05% on weekdays and 1.48% on weekday peak times.

### 6.1.2 Winners and Losers under TOU Tariffs

As smart metres are deployed across deregulated domestic energy market, TOU tariff plans could become more common. If consumers respond to price signals, TOU tariffs and other methods of time-dependent pricing plans may be mutually beneficial, resulting in cost savings for both energy producers and consumers. For a viable TOU design, there are two main requirements:

1. To accurately represent changes in both electricity prices and grid constraints so that customers' reactions can be affected for both generation and grid benefits.

2. To allow consumers, who use DR, gain the rewards of the TOU tariff deployment.

Nevertheless, because of customer engagement and future peak shifting capability, these tariffs are likely to have both favourable and unfavourable financial consequences for users. Finding potential energy reducers or non-reducers ahead of time will help to improve the design of a TOU programme, thus increasing the benefit of its outcome.

Using only ex ante data, this research develops a statistical model to classify the features of so-called winners and losers - or homes that will be better or worse off under a TOU tariff. The accuracy of model achieves a reliable standard using historical power demand data and basic homes characteristics. If online activity information is accessible, this accuracy can be enhanced even further, justifying digital engagement and gamification in TOU schemes. This work also introduces a new public dataset (CAMSL) of 1568 Japanese households, which includes historical smart metre data, household characteristics, and online activity variables collected during the TOU engagement intervals in 2017 and 2018.

### 6.1.3 Data Driven Model for Rooftop Excess Electricity Generation

This work proposed an integrated data-driven Gaussian Process model for daily excess electricity generation. The research provides a structure for developing a model by classifying useful features, as well as a method for reducing the number of datasets required without sacrificing forecasting accuracy.

The work shows how to optimise the necessary set of features, training data intervals, and number of homes, all of which are directly related to data collection costs and computational capacity. The combination of four features, two of historical excess-generation data and two of weather parameters, is demonstrated to be reliable. Further, for robustness against seasonal variation, a year of data collection from 18 homes yields the optimum number of training datasets. This study also exposes a major flaw in the decoupled approach for calculating excess generation. The developed model has a significantly better prediction output than the decoupled value (daytime generation minus daytime consumption), which has an inherent tendency to underestimate significantly. The outcome confirms the need for an excess-generation model.

## 6.2 Limitations

Due to various constrains in the real world, there are some limitations in our works which the author has recognised.

### 6.2.1 External Validity

One more major shortcoming of this study is that the proposed models are trained and tested on a single dataset. Power demand is believed to vary considerably by region, year, weather, household type, appliance availability, social crisis, pandemic, etc.

Extensive testing using multiple datasets of various locations and conditions is not easily accomplished. As previously mentioned, the lack of valid public datasets further complicates academic analysis. In industries, energy producers have recently collected vast amounts of data on power demand and other metrics (which they would not make public), suggesting that further validation should be possible. Additional analysis for diverse datasets (different numbers of homes, locations, and parameter configurations, for example) to increase external feasibility is also needed if an energy provider wishes to adapt this model to their target market.

### 6.2.2 Limitation for CAMSL dataset

One downside of Chapter 4 is that the control group's pool of participants in the CAMSL dataset was not completely chosen randomly during the selection process, which may incorporate unintended biases. Due to the commercial nature of this research and our inability to participate in the design of the control group, recruiting participants in a completely randomised academic way was beyond the scope of this trial's investigation power. Given that the smart meter has already hit the practical stage, obtaining a completely randomised control group (as is typically the case during the early stages of a pilot trial) is more challenging; hence, the suggested solution is considered to be a viable option. However, there are a few alternative strategies for constructing a successful control group, and therefore another trial for developing a control group using the CAMSL dataset would be strongly regarded.

A further limitation of the CAMSL dataset is that the control group was distinguished from the trial group by the fact that they remained on the traditional flat-rate tariff and did not communicate with a digital interface or gamification. Although this study's approach adequately accounted for differences in behaviour due to a variety of causes, it was unable to distinguish the effect of the digital interface from the financial incentive in the end results. Because of this, further analysis is needed to disentangle the relative impacts of these elements, which can then be used to evaluate the influence of various financial rewards, as well as the effectiveness with which these structures are conveyed through the digital interface and gamification. Gamification and methods of constructive communication between energy producers and customers are, and will continue to be, critical and useful components of incorporating intermittent renewable energy supply in the years ahead; consequently, further studies should be conducted to study the in-depth causal effects of gamification on consumer behaviour.

Finally, the causality link between online engagement and reduction rate cannot be fully justified in the current dataset. In order to more fully prove this link, there would need to be investigation into the result of further trials. For example, if a trial where companies try to increase the online engagement of losers (i.e., households who did not reduce their peak consumption in the current trial) results in their consumption significantly decreasing due to the intervention, then the causality link would be established more solidly.

### 6.2.3 Deeper Examination on a GP Model

Certain decision-making factors in modelling framework of Chapter 5 are still not entirely justified. The immediate next stage in model construction would be to thoroughly validate each stage and to minimise the number of explanatory variables without sacrificing accuracy. To begin, a GP model selection is more justified when compared to other probabilistic forecasting modelling methodologies illustrated in Section 2.2.2. A comparative analysis using different probabilistic models as we did in Chapter 3 could have done to choose the best model.

Moreover, if it is determined that a GP model is the most appropriate for this purpose, other covariance functions should be taken into account. Since GP is absolutely defined by its mean and covariance functions, selecting a covariance function is critical for any further GP study. The squared exponential was selected for this study, assuming correlation between each data point. For developing rather smooth functions, the squared exponential for covariance function is thought to be suitable. Nevertheless, there are several covariance functions for GP. We could analyse alternative covariance functions, evaluate their properties, and determine if the squared exponential is truly the best covariance function for this research.

Similarly, additional opportunities for development should be considered, such as minimising features (explanatory variables), examining seasonal fluctuations, and evaluating the model's performance at different time and spatial resolutions. Seasonal variation can be included to determine the optimum number of data points and observation time length, while this study demonstrates that 1,000 data points are adequate to replicate this model's accuracy. Throughout this research work, the model's extrapolation robustness should be evaluated further.

## 6.3 Future Work

By introducing three modelling approaches and one new dataset (CAMSL), this study has successfully presented the identified four main research gaps despite aforementioned limitations . Nevertheless, there are a variety of ways through which they can be further enhanced, and additional research can be done to gain further information. This section summarises some suggestions for future research.

### 6.3.1 A model for more flexible DR tariffs

To the author's best knowledge, Chapter 3 is the one of the first forecasting model to incorporate the users' load adaptation under different TOU tariffs. However, one major flaw in this thesis is that it restricts the study's scope to gain insights into the consumer's behaviour with a static TOU tariff. A static TOU tariff - in which prices vary over time spans but remain constant for a set period of time (generally many months) - is previously believed to be favoured by consumers, as supported by previous literature (Schlereth et al. [239]). A national study in the UK (Nicolson et al. [197]) examined the data suggesting that over a third of bill payers are in favour of switching to a 3-tiered smart time of use tariff, indicating a sizeable potential market for a static TOU tariff.

On the other hand, with the intention of adding a significant portion of intermittent renewable generation power - and hence more volatile production costs - electricity retailers might prefer to offer a more flexible DR tariff (dynamic TOU tariff or demand response tariff) where prices are able to adjust in response to supply prices. This problem will be even more complicated if customer has new controllable capacity such as from heating/cooling system, residential batteries and electric vehicles, which could automate some of these load shifting activities. A study of a public acceptability of domestic demand-side response in the UK (Fell et al. [94]) suggested that such a direct load control can be favourable to residential customers within tight bounds and with override ability, showing that dynamic TOU tariff (otherwise the least popular tariff) can be as acceptable as a static TOU tariff .

There are very limited load forecasting modelling studies for a static TOU tariffs as discussed in this thesis, thus as expected there are very few modelling works which incorporate some automated load behaviour with batteries and electric vehicles; a model for electrical load of a home comprising of a home energy storage, a PV generator, and an electric vehicle in Arens et al. [15]; and a model for power consumption of a single home composed of PV panels and energy storage device in Ahmed et al. [6].

Some of modelling works designed for static TOU tariffs might be useful for these emerging problems, however further modelling works dedicated for these problems is strongly encouraged and will have a high demand in the near future.

### 6.3.2 Live-stream Smart Meter Dataset

The latest public dataset for demand side management was obtained in 2015 as discussed in Chapter 2. CAMSL dataset presented in Chapter 4 and Appendix 1 is collected in 2018, thus the newly obtained CAMSL dataset will be highly valued for future researchers. However, CAMSL will be outdated shortly due to various sociological changes such as Covid-19 and potential installations of electric vehicles and home batteries.

In particular, Covid-19 has considerably affected the load demand, and might change some of people's activities and behaviour for the long run. During the Covid-19 pandemics, numerous countries consumed very low energy as lockdowns took effect (Gillingham et al. [106]). The closure of major social meeting sites has resulted in a reduction in the government and industrial sectors' energy demands. Additionally, the normal demand pattern would be different on weekdays and weekend but with the pandemic, movement of typical residential consumers was restricted and load profiles showed almost similar behaviour on both weekdays and weekends (Chen et al. [43]). Some of these reduced loads will revert once the pandemic is over, but some will not since our lifestyle has changed in the process. Such an inconsistency of load possibly outdated the majority of our historical data collected in pre-pandemic era, and this might cause severe effects on future load modelling works. A study (Xie et al. [297]) demonstrated a way to exploit the value of data in pre-/post-pandemic by focusing on the bidirectional interaction between human and buildings. Thus, these data will not be completely wasted, but there is still a high demand for the new dataset.

The author suggests an approach to overcoming this post-pandemic historical data shortage problem. As of today, millions of smart meters are capable of live-streaming continuous electricity consumption data everyday, and such an up-to-date dataset is the one of the best ways to catch up with such sociological changes in electricity consumption. Therefore, any new public dataset which obtains the explicit customer consent for a certain time period (past and future) will be highly valued by the researchers. This live-stream dataset will be relatively feasible from customers who has installed a 2G smart meters, which usually have the capability to communicate directly with consumer devices. This might give researchers direct access to the smart meter dataset without the secondary involvement of energy suppliers.

The author will keep on working in this sector after this thesis, and will explore the possibility of generating such a live-stream dataset in Japan. I will be delighted to see similar activities across different countries.

### 6.3.3 Statistical Moments

In Chapter 3 and Chapter 4, the effectiveness of statistical moments are demonstrated, and to the author's best knowledge, our work in Chapter 3 (published as Kiguchi et al. [152] in 2019) was the first work to present the importance of statistical moments for load forecasting modelling. Specifically, as shown in Table 3.7 and Table 4.7, these features contributed to the model accuracy significantly. Hence, it is suggested that statistical moments capture effective features of load profiles without using many hand-crafted features as mentioned in Chapter 2. This can be beneficial to not only reduce manual work necessary to prepare many features but also to keep the size of the models relatively small, which can result in less time to re-train the models when new data arrive. To further generalise this approach, more in-depth studies must be conducted. For example, recently, Fayaz et al. [90] showed that using the statistical moments for the input to neural networks can result in nearly 50% better prediction of short-term energy consumption in a residential building, compared to the model excluding them. Similarly, it will be a useful result to demonstrate the efficacy of statistical moments if the accuracy of the model excluding them is reported in our problem settings.

Note that there is a requirement to collect longitudinal data to prepare statistical moments as the model's feature since they are behavioural features over a certain period (e.g., several months). This constraint causes a fundamental limitation: the proposed approach might not work properly at a time when the distributions from which the statistical moments are derived are changing rapidly, for example, due to Covid-19. Thus, a live-stream smart meter dataset which enables a regular update to these variables and the subsequent re-training of the models is similarity crucial for future modelling works. The applicability of statistical moments for load forecasting/management modelling will be further investigated in the future work as our work is the one of the earliest to demonstrate its potentials.

### 6.3.4 Individual Load Forecasting Accuracy under a TOU Tariff

In Chapter 4, the prediction accuracy of load demand at an individual level is actually low, thus we use a binary approach to evaluate the forecasting accuracy. In many practical situations, individual load forecasting is not the primary objective of electricity providers when designing TOU tariffs and optimising energy procurement, since their primary objective is aggregated load profiles. However, the precise estimation of peak load reduction as a result of the individual-level implementation of a TOU tariff is still critical for a variety of reasons. For example, it is critical to consider what a household's energy bill will look like with any changes to their everyday life habits under a TOU tariff. A binary result demonstrated in Chapter 4 is not able to provide a estimation of the future energy bill to each customer.

As a quick potential improvement, a probabilistic model such as Gaussian process could perform better. I however suggest that more thorough examination into the causes and probability of peak shifting at the individual level is required for better individual modelling while still minimising demographic variables.

## 6.4 Policy Implication

Throughout the intensive works on examining TOU tariff potential for the energy transition, the author ends the thesis with commentary on some of the policy implications.

### 6.4.1 Demand for Public Dataset

Limited availability of the public dataset slows the further modelling work in this area, and inconsistency of load patterns in pre-/post-pandemic environments makes this problem even more severe.

Energy companies have accumulated enormous amounts of historical electricity consumption data from millions of smart meters but they are reluctant to publish it or collaborate with external researchers. Although they often cite privacy concerns as the major barrier for this, the author feels that their lack of policy support for data utilisation is the actual reason for this. For example, European Data Protection Supervisor states that power data usage patterns obtained from smart meters can reveal much more than how much power is being used: the use of household appliances is an indicator of human behaviour, and allows for the identification of individuals. The operation of smart meters therefore entails the processing of ‘personal data’ and needs to be in line with the EU’s General Data Protection Regulation (GDPR) Supervisor [262].

To the author’s best knowledge, most industry professionals would disagree with the concerns above as the information potentially unveiled from half-hourly settlement is very limited and not valuable for these concerned applications. Nevertheless, because the privacy breach penalties are so harsh neither most companies prefer not to risk sharing smart meter data. If policy maker would express determine that half hourly smart meter data is not personally identifiable, then the the utilities may feel better about sharing.

The author suggests that government standardised guidelines/rules of data sharing consent towards public dataset participation will result in more projects and innovation in this field.

### 6.4.2 Demand for TOU tariff roll-out

Despite the large potential of TOU tariffs toward promoting carbon neutrality, we cannot force consumers to switch to a TOU tariff without their consent in the real world. Particularly in the competitive deregulated energy market such as the UK and Japan, energy companies are reluctant to sell a TOU tariff, which requires more time and energy to educate the customer to the benefits and more risk of adverse outcomes. It is a known point of competitive differentiation to only offer simple, easy to understand tariffs, and some companies are worried about losing potential customers if their competitor takes the path of providing a simple single-rate tariff.

On the other hand, some countries and states such as Spain, Italy, Ontario and California successfully managed to implement TOU tariffs with the majority of customers. The above-mentioned countries and states are accomplishing large roll-out of TOU tariff plans by making it a default choice or by embracing market-driven innovation. As a default option, users are able to transition away from a TOU tariff plan should they choose. In market-driven innovation approach, smart devices can help customers maximise potential savings and, by automating the procedure, save them the time and effort associated with constantly monitoring and adjusting to tariff changes.

In Spain, about 40% of domestic users are on dynamic TOU pricing plans - much more than in the rest of the Europe (Hussain [134]). This is because the government decided to roll out the dynamic TOU tariff plan as the regulated default pricing plan for small customers. Likewise, in 2012, Ontario became the only province in North America to make TOU pricing plans as the default choice. Over the next four years, the participation rate increased to about 89 percent. The California Public Utilities Commission (CPUC) also directed the government's three investor-owned utilities (IOUs) to move to "default" tariffs by 2019, which would require users to pay TOU prices until they opt out (Trabish [270]). Additionally, the pilots contained two protection schemes for customers. The first is a "shadow bill" that indicates whether clients would benefit more from the TOU rate versus their previous rate. The second is an assurance that users who would have benefited from greater savings under the previous rate will be compensated for the difference during the first year of the shift.

A large scale of TOU tariffs will open a door to further demand side management opportunities. For example, in California, behind-the-meter battery installations are achieving the cost parity due to these TOU tariffs; therefore, a large scale of battery installations are underway. As a result, one of the leading company named STEM, Inc (STEM) is newly listed at the New York Stock Exchange in 2021, and their market cap is over 3 billion dollars as of today (November 2021).

The author suggests government driven encouragement of TOU tariff roll-outs at the national level is needed, and this action is necessary to fully incorporate more intermittent renewable energy power stations, and battery installations.

# Appendix A

# CAMSL Dataset

## Overview

CAMSL is the public dataset for a TOU tariff intervention study using smart-meter data including, pre, during, and post TOU intervention periods. The CAMSL dataset was generated based upon the introduction of a TOU tariff trial in 2018 (Looop TOU campaign [171]) by Looop Inc.(a energy retailer) and SMAP ENERGY Limited (smart meter data analysis company in UK) (SMAP Energy Limited [250]). This dataset is called CAMSL: CAMBRIDGE-SMAP-LOOOP given that this was a joint research programme between Looop Inc., SMAP ENERGY Limited, and our research group at the University of Cambridge. Note that this is a commercial trial conducted by two companies to examine the opportunities for a TOU tariff.

The author's contributions:

- Actively consult on the creation of the commercial trial design.
- Implemented features to obtain user consent for a future academic use.
- Process the collected raw data and prepare the dataset, including creating documentation and the github repository.
- Manage the CAMSL dataset for the future researcher access.

The collected data was preprocessed to exclude customer data which had missing points during the trial period, including those who quit their participation in the middle of the trial. As a result, the CAMSL dataset provides 1423 customers data in total, 1023 as TOU customers, and 400 as Control customers. TOU tariffs are as follows:

- TOU: peak rate is equal to 35 JPY/kWh, off-peak rate is 20 JPY/kWh

| | time | timestamp | consumption |
|---|---|---|---|
| 0 | 2017-06-01 00:00:00 | 0.0 | 90.0 |
| 1 | 2017-06-01 00:30:00 | 0.5 | 20.0 |
| 2 | 2017-06-01 01:00:00 | 1.0 | 10.0 |
| 3 | 2017-06-01 01:30:00 | 1.5 | 30.0 |
| 4 | 2017-06-01 02:00:00 | 2.0 | 40.0 |

Fig. A.1 Sample data of the consumption data. Each row represents half hourly consumption data.

- Control: peak rate and off-peak rate are 26 JPY/kWh

The dataset also includes raw data of 3337 customers who did not participate in the TOU trial.

## Table of Contents

The entirety of the CAMSL dataset is publicly available on the web: https://github.com/smapenergy/CAMSL. The CAMSL contains the items shown in Table A.1. The dataset is available for free for both academic and industrial researchers to access upon the request.

| File name | File type | Description |
|---|---|---|
| README | text | instruction text |
| consumption_data | zip | from June 2017 to December 2018, 1023 TOU users and 400 Control 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 |
| 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 |

Table A.1 Items in the CAMSL TOU dataset

## Consumption Data

The file "consumption_data.zip" contains csv files for each household. Each csv file has a monthly data and three columns: *time*, *timestamp* and *consumption*. Each row represents a half-hourly consumption data. Figure A.1 shows a part of the data table. Figure A.2 shows an average load curve for a specified month.

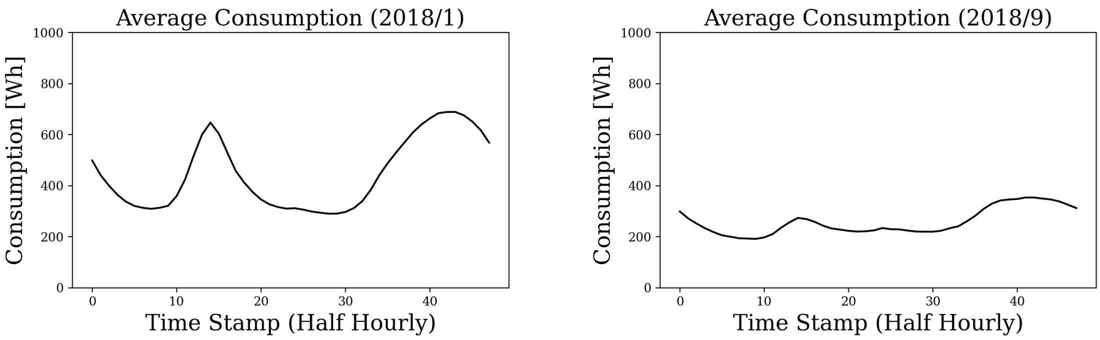


Fig. A.2 Load curves of average consumption of all users in different months, January (left) and September (right).

| | id | house_type | number_of_residents | tou |
|---|---|---|---|---|
| **0** | 137 | 2 | 1 | 1 |
| **1** | 162 | 1 | 3 | 1 |
| **2** | 216 | 1 | 4 | 1 |
| **3** | 234 | 2 | 1 | 0 |
| **4** | 250 | 1 | 2 | 1 |

Fig. A.3 Sample data of the customer information. Each row represents data of one household. The table has 1423 rows that are equal to the sum of the numbers of TOU customers and Control customers.

# Customer Information

The file "customer_info.csv" has 1423 rows and four columns: *id*, *house_type*, *number_of_residents* and *tou*. There are no missing data in the table. Each row is data for each household, whose identifier is shown as *id*. The column *house_type* means the type of the household (1: detached house, 2: flat). The column *number_of_residents* represents the number of people living in the house. Finally, *tou* is a flag showing whether the household is a TOU customer or not (1: TOU customer, 0: Control customer). Figure A.3 shows a part of the data table. Figure A.4 shows the distributions of *house_type* and *number_of_residents* in the dataset.

# Web Information

The file "web_info.csv" has 1023 rows and three columns: *id*, *sessions* and *average_session_duration*. There are 395 households who miss these values, shown as *NaN* in the following Figure A.5.

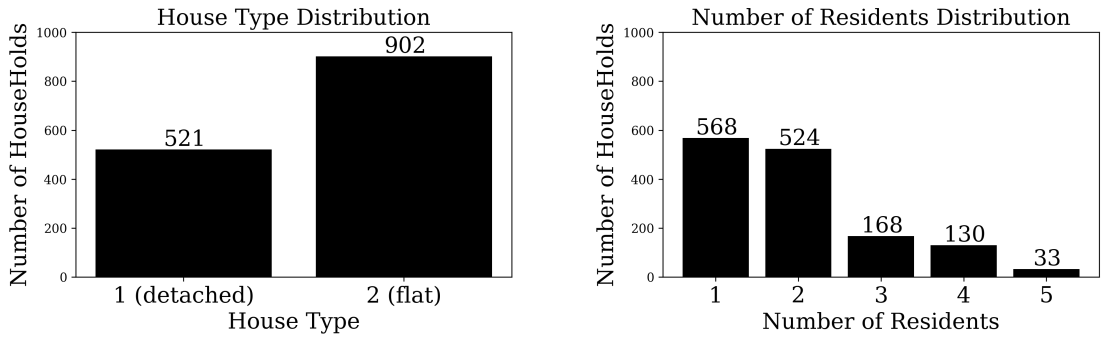


Fig. A.4 The number of households by house type (left) and number of residents (right).

| | id | sessions | average_session_duration |
|---|---|---|---|
| **0** | 137 | 12.0 | 00:00:31 |
| **1** | 162 | NaN | NaN |
| **2** | 216 | 4.0 | 00:00:11 |
| **3** | 250 | 1.0 | 00:01:20 |
| **4** | 267 | 21.0 | 00:00:13 |

Fig. A.5 Sample data of the web information. Each row represents data of one household. The table has 1023 rows that are equal to the numbers of TOU customers.

These are the households who did not visit the web page during the TOU period. Each row is data for each household, whose identifier is shown as *id*. The column *sessions* means the number of times the user visited the web page during the TOU period. The column *average_session_duration* represents the average time the user spent on the page by each visit. Figure A.5 shows a part of the data table. Figure A.6 shows the distributions of *sessions* and *average_session_duration* in the dataset.

## Temperature in Tokyo

The file “temperature_Tokyo.csv” has 13896 rows and two columns: *temperature* and *time*. There are no missing data in the table. Each row is hourly temperature data. The column of *temperature* shows the hourly average temperature measured in Tokyo, Japan, from June 2017 to December 2018. The column of *time* shows the time that the corresponding temperature was measured. Figure A.7 shows a part of the data table. Figure A.8 shows the sample average daily temperature of June of 2017 and 2018.

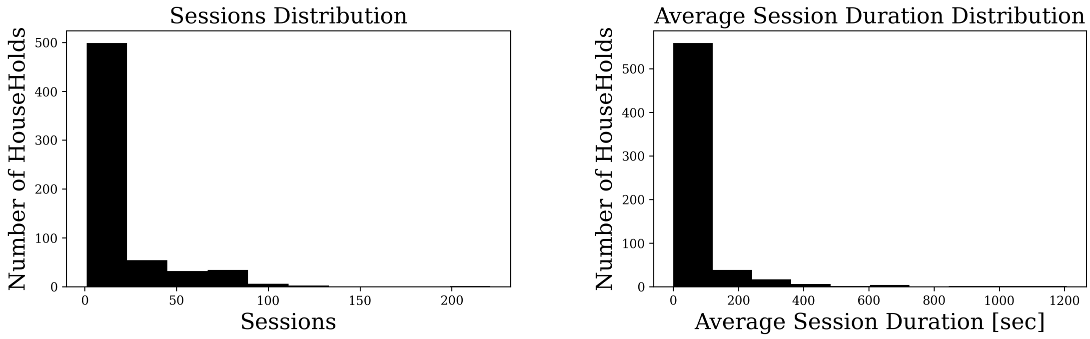


Fig. A.6 The number of households by sessions (left) and average session duration (right).

| | temperature | time |
|---|---|---|
| **0** | 21.7 | 2017/6/1 1:00:00 |
| **1** | 21.9 | 2017/6/1 2:00:00 |
| **2** | 21.9 | 2017/6/1 3:00:00 |
| **3** | 19.6 | 2017/6/1 4:00:00 |
| **4** | 20.3 | 2017/6/1 5:00:00 |

Fig. A.7 Sample data of the temperature information. Each row represents hourly average temperature measured in Tokyo. The table has 13896 rows.

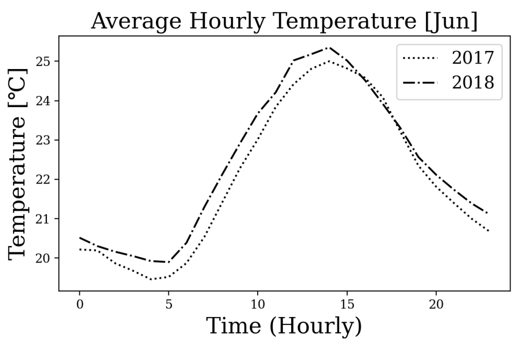


Fig. A.8 Average daily curve of June of 2017 and 2018.

| | date |
|---|---|
| 0 | 2017-01-01 |
| 1 | 2017-01-09 |
| 2 | 2017-02-11 |
| 3 | 2017-03-20 |
| 4 | 2017-04-29 |

Fig. A.9 Sample data of the Japanese holiday information. Each row represents the date for Japanese national holiday. The table has 32 rows.

| | dt | c | consumer_id |
|---|---|---|---|
| 0 | 2017-06-01 00:00:00 | 0.1 | 366 |
| 1 | 2017-06-01 00:30:00 | 0.1 | 366 |
| 2 | 2017-06-01 01:00:00 | 0.1 | 366 |
| 3 | 2017-06-01 01:30:00 | 0.1 | 366 |
| 4 | 2017-06-01 02:00:00 | 0.0 | 366 |

Fig. A.10 Sample data of the consumption data. Each row represents half hourly consumption data of a certain household. The table has 92741904 rows.

## Holidays in Japan

The file "holiday_Japan.csv" has 32 rows and one column: *date*. There are no missing data in the table. Each row represents the date for Japanese national holiday from January 2017 to December 2018. Figure A.9 shows a part of the data table.

## Non TOU data

The file "non_tou.csv.zip" has 92741904 rows and three column: *dt*, *c*, and *consumer_id*. There are no missing data in the table. Each row represents the consumption data at a single date time of a household. Figure A.10 shows a part of the data table.

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