Exploring Smart Grid Time-of-Use Tariffs using a Robust Optimisation Framework

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***Abstract*—This paper describes a study in Smart Grid Tariff Design. We use historic Smart Meter electricity usage data and Representative Load Profiles (RLPs) to explore Time-of-Use (ToU) tariffs. We consider the problem from the perspective of a supplier who wishes to set tariffs to maximise revenue, and has to anticipate responses from consumers who wish to minimise their costs. This is a typical bilevel optimisation problem, but with additional challenges as consumers have uncertain electricity usage. We create test RLP instances using historical Smart Meter data and demonstrate the use of a robust optimisation framework to address uncertain usage patterns. Our modelling and optimisation approach offers a framework for suppliers, system operators and innovators to explore and evaluate potential ToU market offerings.**

***Index Terms*—Robust optimisation, electricity representative load profiles, smart meter data, smart grid tariff design**

I. Introduction

EU member states are required to implement smart meters under the 2009 Third Energy Package wherever it is cost-effective to do so. Smart meters have been deemed to be cost effective in Ireland and are currently being rolled out using the high level design outlined in [1] with a target completion date of 2024.

In this paper we explore innovation in electricity tariff designs. Tariff design is sometimes framed as a bilevel optimisation or Stackleberg Game problem, where a supplier (leader) sets prices, and consumers (followers) react accordingly. In deregulated electricity markets there are multiple actors which leads to even more complex optimisation problems. The Multi-LeaderFollower-Game is considered in [2] where leaders play a noncooperative competition and each of the leaders problems is at least a multilevel problem.

Research Question: Given access to smart meter electricity usage data and market costs, can a robust optimisation framework be used to explore tariff designs for a supplier to minimise deviation from revenue targets in the face of consumer usage uncertainty?

In this case study we focus on the Republic of Ireland and household (domestic) consumers. We present a robust optimisation (RO) framework to explore the tariff design solution space. We present analysis and discussion of computational tests using publicly available high resolution electricity consumption data. Our results show that the framework offers useful insights on tariff solutions. Our mathematical models and solution algorithms are transferable to other jurisdictions.

II. Smart Grid - Smart Meter enabled Innovation

As the electricity system becomes more digitised, more data from consumers and their end-use applications and appliances will become available. Additional instrumentation of the "last mile" can aid planning and management of the grid. Smart meters can enable customers to take more control of and make better informed decisions about their energy usage and their electricity supplier choice. Smart Grid products can be developed using machine and statistical learning techniques. New markets are opening up for services to be offered to system operators and to consumers. There are opportunities for new value-add services for demand response units, and for energy efficiency and cost reduction for consumers. By extracting value from consumption data, suppliers can reduce their own risks in short-term markets.

There are significant challenges to estimate customers consumption needs in light of the adoption of low carbon and information technologies, distributed renewable generation and changing lifestyle patterns. There are additional privacy and cyber security issues. Suppliers, and in fact all market participants, will require more intelligent data driven techniques to forecast demand patterns to extract value from the market and to avoid exposure to volatile wholesale prices and variable renewable generation.

Network operators need greater visibility of the high and low voltage networks to aid decisions on network investment. Anonymised publicly available data is needed to facilitate innovation by allowing prototyping and evaluation of new services. The challenge to transition to a future low carbon electricity system in a way that is sustainable and fair to all can be tackled by exploring and evaluating services and products virtually using analytics.

A. Ireland's Electricity Market

The Commission for Regulation of Utilities (CRU) is the independent energy regulator in the Republic of Ireland. The CRU regulates the network charges associated with the electricity transmission and distribution networks. Their role is to ensure that customers and network users receive value

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for money while the network companies achieve a fair return on their activities.

There is one Distribution System Operator (DSO) and one Transmission System Operator. There are several generators and suppliers. New entrants to the market in Ireland include aggregrators and analytics innovators.

Electricity tariffs in the retail electricity markets are fully deregulated for all consumers. Hence there is no standard or benchmark tariff. In markets where former monopolies retain significant market power, regulators may continue to regulate tariffs to foster opening the market to new competitors. Suppliers are free to set their tariffs to cover wholesale electricity costs, network charges and the supplier's own operating costs. Suppliers buy electricity from the Integrated Single Electricity Market (I-SEM) at the System Marginal Price (SMP) to meet the estimated demand of their customers (consumers). I-SEM is the wholesale electricity market for the whole island of Ireland. It aims to integrate the all-island electricity market with the EU Internal Energy Market for electricity. Electricity generators with capacity above 10MW must bid in to the pool market. Post-Brexit arrangements have yet to be determined.

There are approximately 2M domestic consumers in Ireland who are free to select their energy supplier. Suppliers currently offer fixed or night time saver schemes with introductory discounts for new customers. Customers generally sign a one year initial contract, and while they can they switch contract, the data show the majority default to standard tariffs [3].

B. Standard and Representative Load Profiles

Standard load profiles (SLPs) are representative load profiles which are used for market balancing and network planning purposes. Load data from sample meters is collected, anonymised and aggregated on behalf of the CRU and processed annually to create base SLPs for the following year. This is similar to the approach in [4]. However, SLPs are based on aggregations of at least 100 customers so under represent consumer activity on the edges of the low voltage (LV) network.

Historically high resolution consumer load data has not been publicly available to understand consumer electricity usage at the individual consumer level. High resolution data from individual smart metered consumers can be used to create better bottom up models and to generate better understanding of consumer and network needs and activity.

The importance of understanding electricity consumption patterns is emphasised in [5] and [6]. A clear distinction between weekday and weekend usage is observed in [7] using statistical techniques to analyse half hourly data of Irish consumers during a smart meter trial. Unsupervised machine learning techniques such as self organising maps and k-means are used in [8] to characterise and cluster 15-minute resolution data of 165 consumers of a Portuguese company. Any new load shape or altered annual electricity consumption of domestic customers lead will lead to altered utilisation of the network assets particularly during peak load conditions [9].

Currently consumers in Ireland have low visibility of their usage. Meter readers call to consumer premises up to four times a year. The CRU requires price comparison websites and suppliers to use a common annual average consumption value [10] of 4,200kW per annum, down from the previous value of 5,300kW. The decrease is down to changing demographics and lifestyles [11]. The regulator decided not to use a low, medium and high classification as consumers do not know their actual consumption, but did consider values of 2,100, 3,500 and 5,200kWh/annum respectively.

Questions arise of how suppliers should distribute the industry average against representative profiles to design time-of-use tariffs, and whether their own consumer base is similar/dissimilar to the average consumer.

C. Smart Meters in Ireland

The CRU has mandated ESB Networks (the DSO) to be responsible for the implementation of the national smart meter roll-out plan. The DSO will be responsible for the transfer and safe keeping of smart meter data. Initially analogue meters will be replaced by meters with data storage and communication capabilities. Fig. 1 shows the high level design. Daily transfer of aggregated data will begin in 2021. Data will be transferred over the 2G mobile network. By agreement consumers may choose to allow higher resolution half hourly to be transferred once a day. This opens up the possibility for energy analytics innovators to carve out a new role in modelling consumer load data to better understand and extract value for both the consumer and other market participants.

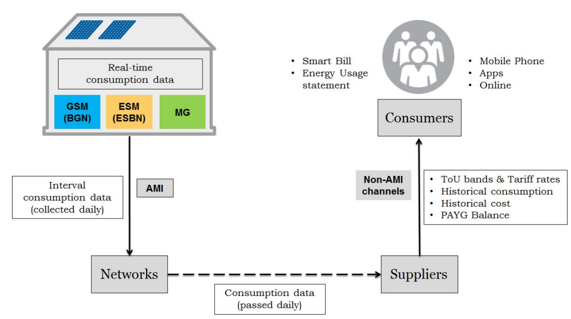

Fig. 1. Smart Meter High Level Design, Ireland [1].

D. Innovation, New Markets, dealing with Uncertaity

Since deregulation of electricity markets, vertically integrated monopoly companies have replaced by demerged specialised companies with individual profit maximisation objectives in generation, transmission, distribution, or retail sale of electricity. Traditional optimisation methods aimed at minimising expected costs without accounting for risk and market behaviour are now redundant citerocha2012multistage.

The partitioning of former monopolies restricts data sharing and collaborative planning for the whole system and hence introduces more uncertainty for the individual companies. Digitalisation of the electricity grid is an enabler of innovation, particularly through the sharing of anonymised research data.

The publication of usage and network data raise concerns about privacy for the consumer, and cyber security of the grid. The EU supports multiple indicatives to address these issues. The European Technology and Innovation Platform: Smart Networks for Energy Transition (ETIP SNET) Vision 2050 document synthesises the views of its industry and academic members [12]. The EU Smart Grid Task Forces have addressed specific areas such as privacy, data protection and cyber-security in the smart grid environment.

Time-of-use and dynamic tariffs have been trialled in several jurisdictions. Price signals can aid peak shaving and stimulate demand response. However, in general consumers have been slow to adopt these newer pricing regimes and consumers prefer fixed rate to dynamic prices. Reasons for, and opportunities to increase acceptance of dynamic pricing plans are described in [13]. Part automation, and ease of use are important considerations.

Reference [14] analyses domestic users' electricity demand and the System Marginal Price (SMP) of Irelands Single Electricity Market to estimate the wholesale risk associated with possible tariffs. A genetic algorithm with a stochastic fitness function searches for Time-of-Use tariffs to minimise wholesale risk for a supplier in residential markets.

A framework for modelling and solving optimisation problems with hierarchical structures is described in [15]. The first optimisation problem (the supplier upper level problem) contains constraints specifying that the solution must be optimal to a second optimisation problem (the lower level consumer problem). The values of the decision variables of the first problem influence the optimal solution of the second problem and vice-versa. Different modelling approaches can be used depending on the followers' behaviour depending on whether it is cooperative or aggressive. The interaction between suppliers can be cast as a game where suppliers set prices and consumers react. A bilevel stochastic mixed integer program is tackled via a novel preprocessing procedure in [16] where elastic loads couple all time periods of a given day. An alternative approach using extended goal programming is described in [17], complex decision problems involving multiple conflicting goals are modelled using a meta-goal framework to balance goals from a network of stakeholders, all of whom have some influence on the decisions of the problem.

Reference [18] proposes a game theoretical model accounting for the Stackelberg relationship between retailers (leaders) and consumers (followers) in a dynamic price environment. The authors compare the dynamic pricing scheme with fixed and time-of-use pricing and find that the dynamic pricing scheme benefits the retailer reducing its costs through efficient load-shifting, but that real-time pricing is less convenient than fixed and time-of-use price for consumers.

Stochastic Programming allows us to tackle optimisation problems that involve uncertainty by creating scenarios of sequential linked stages of probable outcomes. In some cases the probability distribution of the data may not be known, but we may have knowledge that the data belong to a given uncertainty set. We wish to find optimal solutions such that the constraints hold for all possible values of the uncertain data. In this case Robust optimisation (RO) provides an optimisation framework that aims to find optimal solutions that remain feasible for all outcomes of the uncertain data [19], [20].

Reference [21] describes the use of RO to design time-of-use rate demand response programs under market price uncertainties and to design optimal bidding strategies for electricity retailers. Reference [22] proposes a two-stage two-level model for energy pricing and dispatch by a smart grid retailer. The authors model a risk-aversive energy dispatch accounting for market price uncertainty by a linear robust optimization with objective parameter value uncertainty. They combine a heuristic with a linear program model to decide enhanced bidding strategies that guarantee a Pareto improvement on the retailers profit over the entire uncertainty set.

III. Methods and Models

In Section II-D we highlighted optimisation approaches for dealing with uncertainty. Since deregulation there has been a focus on cost minimisation of power generation scheduling and bidding problems of generating companies but that less attention has been paid to the procurement of electric energy by retailers to supply end users [23]. The focus of this study is to explore the tariff design framework from the perspective of a retailer. Given access to smart meter electricity usage and market data, we wish to determine a short term tariff regime for a supplier to minimise deviation from revenue and consumer usage uncertainty targets. We foresee a role for short term contracts, where smart meter data can be used to understand and match consumers usage patterns to tariff offerings for periods of one month. In this study we design tariffs by weekday/weekend, time of day and consumer cluster to demonstrate the use of the RO framework.

Consumers wish to minimise their costs of using electricity, so may choose lower tariffs, and/or to reduce usage or change the time they use electricity. Consumers' electricity demand may be estimated but is somewhat uncertain depending on weather, home type and other factors. Consumers currently have little information of knowledge about their usage so are unlikely to know which type of cluster they belong to, the customer "self-classification" problem referred to in [10]. In the smart meter high level design in fig. 1 daily transfer of aggregated data will be the default, but consumers may opt in to allow higher resolution usage data to be transferred. Such data will allow opportunities for greater visibility and analysis of usage patterns at the edge of the network.

We present a robust optimisation (RO) framework to address the short term tariff design problem. We use publicly available high resolution electricity consumption data to prototype our work. We cluster consumers and characterise the clusters by creating RLPs of electricity usage per cluster. This captures some of the uncertainty associated with consumer usage and provides test instances for computational tests of tariff design.

A. Mathematical Model

Consider a supplier who wishes to maximise profits by setting time-of-use tariffs. Let $x_{d,t,c}$ be the tariff set by the retailer on day type $d \in weekday, weekend$, in time $t \in T$, the number of time slots in the planning horizon, for customer type $c \in C$, the number of consumer clusters. $E_{d,t,c}$ is the electricity usage estimated by the RLPs. SMP_t is the wholesale electricity SMP price paid by the retailer at time t, N are the network costs determined by the regulator, and O are the supplier's operating costs. The supplier's profit is:

$$\max_x F = \sum_{d \in D, t \in T, c \in C} x_{d,t,c} \times E_{d,t,c} - \left(\sum_{d \in D, t \in T, c \in C} (SMP_t \times E_{d,t,c}) + N + O \right) \tag{1}$$

We focus on the first term of (1) in this study, the supplier's revenue term, which also gives us the objective function for potential consumers wish to minimise their costs:

$$\min_E f = \sum_{d \in D, t \in T, c \in C} x_{d,t,c} \times E_{d,t,c} \tag{2}$$

We are interested in exploring the tariff design solution space when the electricity usage E is uncertain. We use an RO framework, recall that RO is a useful framework when the problem parameters are uncertain but can be described by some uncertainty set U. Solutions are feasible for all outcome parameter values in U. We associate some uncertainty $ue_{d,t,c}$ with each $E_{d,t,c}$.

The supplier would like to maximise their revenue but must maintain their tariffs competitive with other suppliers. We use decision variables $x^+_{d,t,c}$ ($x^-_{d,t,c}$) to introduce additional flexibility to the RO framework to allow tariffs per time period to deviate above or below a flat baseline cost recovery price P and consider the robust optimisation problem:

$$\min_{x^+, x^-} \phi = \sum_{d \in D, t \in T, c \in C} \left(w^+_{d,t,c} * x^+_{d,t,c} + w^-_{d,t,c} * x^-_{d,t,c} \right) \tag{3}$$

s.t.

$$\sum_{d \in D, t \in T, c \in C} (P + x^+_{d,t,c} - x^-_{d,t,c}) * (E_{d,t,c} + ue_{d,t,c}) \geq Target_L \quad \forall \quad ue_{d,t,c} \in U_{d,t,c} \tag{4}$$

$$\sum_{d \in D, t \in T, c \in C} (P + x^+_{d,t,c} - x^-_{d,t,c}) * (E_{d,t,c} + ue_{d,t,c}) \leq Target_U \quad \forall \quad ue_{d,t,c} \in U_{d,t,c} \tag{5}$$

$$LB_{d,t,c} \leq ue_{d,t,c} \leq UB_{d,t,c} \quad \forall \quad d \in D, t \in T, c \in C \tag{6}$$

$$x^+_{d,t,c}, x^-_{d,t,c} \in \mathbb{R}^+ \quad \forall \quad d \in D, t \in T, c \in C \tag{7}$$

Equation (3) is the objective function to minimise the deviation from the cost recovery prices P. $w^+_{d,t,c}$ and $w-_{d,t,c}$ are weights chosen by the supplier to target price differentials. Equations (4) and (5) ensure tariff solutions are within the target range set by the supplier for all values of the uncertainty sets. Equations (6) are simple box constraints for the RO uncertains which we derive from the smart meter data. Equations (7) are the nonnegativity constraints of the decision variables. Note, we could also place bounds on $x^+_{d,t,c}$ and $x^-_{d,t,c}$ to reflect the elasticity of demand in different consumer segments.

B. Solution Framework

The smart meter data in this study come from a trial in Ireland with almost 5,000 homes [24]. We use the data from the benchmarking period for 3,864 homes, having removed meters with missing or incomplete data. We use the C programming language for data pre-processing. We use the same data reduction and feature extraction approach described in [25]. We use the SAS FASTCLUS procedures to create three clusters of the smart meter consumers using the extracted features. We split the consumers in each cluster 70:30 using 70% to training RLPs by averaging their electricity usage. We use these training RLP instances as estimates of electricity usage $E_{d,t,c}$ for each cluster per daytype and season. We use associated confidence intervals to create simple box constraints (6) on the uncertainty in the electricity usage. We implement the RO model in FICO XpressMP. We then test and evaluate the tariffs on the remaining 30% of each cluster.

IV. Results and Analysis

We present summaries of the smart meter data analysis in this section. Fig 2 shows a dendrogram for the smart meter data clustered by day. Midweek days show the strongest similarities. We can see more clearly that weekdays form one cluster and that weekend days form a second cluster. Within those clusters we can see that there are some differences between the weekdays. Public holidays in Ireland generally occur on Mondays, the dendrogram shows that, for example, Mondays are somewhat dissimilar to other weekdays. The clustering shows that Fridays are also a bit different to the other weekdays. We also see some differences between Saturdays and Sundays. For simplicity in this study, we evaluated a weekday/weekend tariff design.

We created three clsuters using the SAS FASTCLUS. Analysis of the clusters shows they can be characterised as Low, Medium and High usage groups which aligns with the CRU approach [10]. The cluster proportions are [0.45,0.43,0.12]% of the consumers. However, the average usage per cluster is higher than that suggested in [10]. This can be partly explained by changing demographics and lifestyles, a more recent data set would provide a more accurate current picture.

We randomly select 70% of the meters in each cluster to create RLPs for the RO problem. We created (training) RLPs by season and day type for each cluster. Fig 3 shows the RLPs for the three clusters.

All RO models for the training instances solve in fractions of a second. The speed of the optimisation model allows us to evaluate several scenarios in the RO framework.

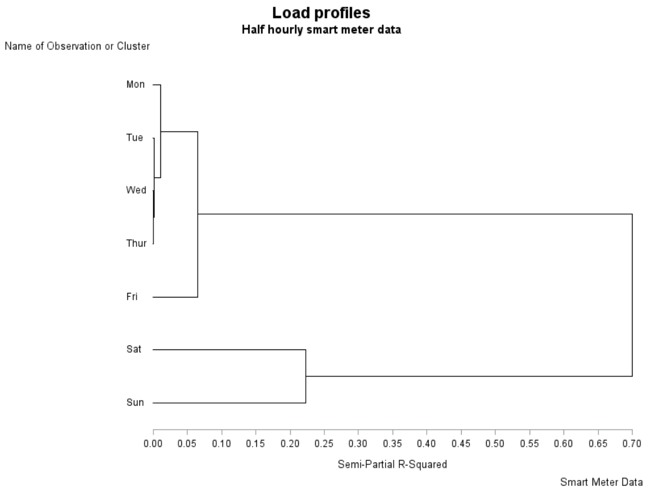

Fig. 2. Day Type Cluster Dendrogram

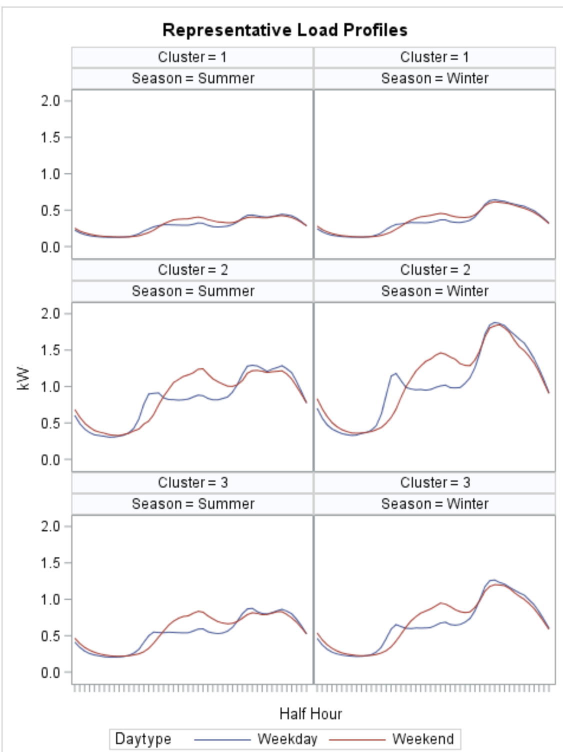

Fig. 3. Smart Meter Cluster Representative Load Profiles

We used the remaining 30% of meters in each cluster to create test RLPs to check the outcome of applying the designed tariff. Recall that the RO approach will find solutions that are feasible for all outcomes of the training RLP uncertainties.

Setting the weights $w^+_{d,t,c} = w^-_{d,t,c} = 1$ returns a flat price for most scenarios, with the price differentials set to zero. By altering the weights we can find tariffs that balance differential price increases with price decreases, and so can target day types or times of peak/offpeak usage.

Table I shows sample results for a scenario with a portfolio of 10,000 consumers with the RLPs shown in Fig 3 and an expected split of [0.45.0.43, 0.12], $w^+_{d,t,c} = 1.25, w^-_{d,t,c} = 1$. Sample values of some of the uncertains in the optimal solutions show the different in electricity usage from the expected RLP.

TABLE I
SAMPLE COMPUTATIONAL RESULTS

Name	Value
Upper Target	€7,423,710
Lower Target	€7,211,604
Expected Revenue	€7,317,657
Outturn Revenue	€10,920,958
Flat price	24.2034c/kWh
x^- Low, Summer Weekday Peak	24.2034c/kWh
x^- Low, Winter Weekday Peak	24.2034c/kWh
x^+ Medium, Winter Weekday Offpeak	6.4788c/kWh
Uncertainty Low, Summer Weekday Peak	0.0175kWh
Uncertainty Low, Summer Weekday Peak	-0.0123kWh
Uncertainty Low, Winter Weekday Peak	0.0175kWh
Uncertainty Low, Winter Weekday Peak	-0.0163kWh
Uncertainty Medium, Winter Weekday Offpeak	0.0035kWh
Uncertainty Medium, Winter Weekday Offpeak	-0.0035kWh

This example uses an upper revenue target to achieve a profit margin of 5% and a lower target of 1%. These margins are set to ensure the revenue exceeds the costs in (1). The expected revenue from the expected demand ignoring uncertainty lies between the two targets. Using the 30% test meters we see that the outturn revenue exceeds even the upper target.

We note that some price decrease differentials effectively set the price to the consumer to zero. While the aggregate outturn revenue is still attractive to a supplier, further analysis is warranted. We note that by aggregating across the entire portfolio, we are effectively encouraging low usage consumers to increase their demand in this extreme example. Other scenarios achieved more balanced solutions, setting for example a modest price increase differential offset during peak periods for high use consumers which is offset by a lower flat price for all consumers.

V. DISCUSSION AND CONCLUSIONS

Careful design of the retail market is needed to balance the profit maximisation goals of retailers with cost minimisation goals of consumers [18]. We identify some limitations of our approach and suggest areas for further research.

We framed the RO problem with independent box constraints for each uncertain. In reality electricity usage data are correlated time series, further research on uncertainty constraints to capture the autocorrelation is warranted.

We used a quite simple clustering approach, further computational experiments to cross validate the RLPs created from the clusters would be useful. Many other approaches are possible and may yield alternative clusters of the consumers. Further characterisation and comparison of the cluster RLPs to industry averages would be beneficial to a supplier to understand their consumer base.

Viewing RO as a leader-follower game the opponent, consumer in our case, increases the uncertain to make the robust constraint as tight as possible. Here, the consumer will use the highest amount of electricity at that price to maintain their desired comfort levels. This "comfort taking" behaviour has been observed in practice when low tariffs are offered. Hence setting tariffs to zero should be further explored to avoid wasteful behaviours.

Our model optimises over the full portfolio of consumers. We have not addressed how the weights of the objective function should be selected. One of the axes of the energy trilemma is *fairness*. Our approach could be linked to works such as [17] to ensure tariffs are balanced in a fair manner.

The age of the data used in our study is also a limitation. Our approach could be evaluated on more recent data. We note that the average use of the consumers in the smart meter trial is higher than the recent regulator industry average [10]. We foresee a role for an "honest broker" energy analytics advisor to match consumers to suppliers' short contracts possibly using pooled industry anonymised data. Access to appropriate data will be needed to enable agility and new ways of working.

Lastly, we have not addressed the role of automation, or whether we expect consumers to actively manage their electricity usage in response to tariffs. There are opportunities to offer consumers smart products to facilitate more intelligent decarbonised flexibility solutions. A level of automation will be required to enable closer to real time smart tariff operation. This in turn requires access to consumers' consumption (and renewable energy source) data in real time. We will also need to build consumer trust in the algorithms and technologies and ensure that the tariffs will be fair.

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