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Smart Meter Tariff Design to Minimise Wholesale Risk

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Abstract

Smart metering in electricity markets offers an opportunity to explore more diverse tariff structures. In this article a Genetic Algorithm (GA) is used to design Time of Use tariffs that minimise the wholesale risk to the supplier in residential markets. Residential demand and the System Marginal Price of Ireland's Single Electricity Market are simulated to estimate the wholesale risk associated with each tariff.

Keywords: Smart Grid tariff design, Genetic Algorithm, Stochastic Fitness function.

1 Introduction

Yield Management (YM) in the telecommunications sector is described in [1] as the application of information systems and pricing strategies to allocate capacity to customers at a price and time that maximises revenue. In this paper, we describe a variant of YM where the objective is to minimise risk for the wholesale operator in setting the price for residential electricity in a Smart Grid (SG).

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2 Electricity Market Operations

The Single Electricity Market (SEM) is the wholesale electricity market for generators and suppliers in the island of Ireland. All electricity suppliers participate in the market. Wholesale electricity prices are calculated in each half hour based on bids submitted by generators. Each generator is dispatched by the Market Operator so as to minimise prices and to meet market demand. As each generator is dispatched, its bid affects the price. The generator with the least competitive bid sets the price i.e., the marginal cost of power. For this reason, electricity prices are referred to as the System Marginal Price (SMP). SMP data for the SEM is available from the SEM Operator (SEMO).

A Smart Metering (SM) system combines an electronic meter with a communication layer for sending consumption data to the network operator. The Irish Commission for Energy Regulation (CER) conducted SM Customer Behaviour Trials (CBTs) [3] with a view to an SM rollout by 2019. Consumption was recorded at half hourly granularity to align with the SEM.

2.1 Smart Grid Tariff Design Problem

Much of the research in the SM sphere focuses on the benefits to the electricity market as a whole - in particular demand side management and on improved forecasting techniques to estimate that demand. We focus however on minimising the risk specific to suppliers in the market. [2] give an account of the financial risks faced by electricity suppliers. These include credit risk, operational risk and also (wholesale) volume risk.

Suppliers enter into financial arrangements to fix the wholesale price of power as shown in Fig.1. Typically this is in the form of a Contract for Difference with a Generator. The supplier quantifies a forward price H_{ij} for expected demand f_{ij} where i is the day and j is the half hour within the day. The combination of purchasing from the SEM pool and the financial arrangement provides a hedge of the wholesale price for the supplier.

A single tariff unit rate is given by $T = \frac{\sum_{ij} f_{ij} H_{ij}}{\sum_{ij} f_{ij}} + M$ where M is the margin applied. However, SM customers could be charged a Time of Use (ToU) price T_{ij} in time slot ij. In addition, the actual amount of electricity used, a_{ij}, may differ from the forecast. Additional (excess) electricity must be purchased (sold) from the SEM pool at the outturn SMP price S_{ij}.

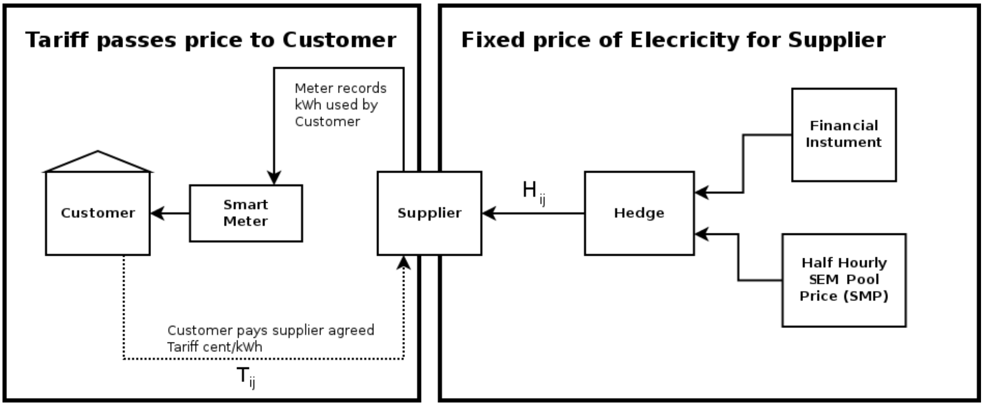

Fig. 1. Hedge of forward electricity prices

2.2 Problem definition

Thus for the period of the contract the supplier will realize a *Profit or Loss* of

$$P(T) = \sum_{ij} (T_{ij}a_{ij} - H_{ij}f_{ij} + (f_{ij} - a_{ij})S_{ij}) \tag{1}$$

Since the values of S_{ij} and a_{ij} are stochastic, the Profit or Loss is also stochastic. We define the *Wholesale Risk* associated with a tariff T as: $Var(P(T))$.

We wish to determine a ToU tariff that minimises wholesale risk:

$$\min \quad Var(P(T)) \tag{2}$$

3 Methodology

3.1 Tariff Structure

Let the set of n days of the contract period be $\mathcal{I} = \{1 \ldots n\}$. Let the set of half hours in a day be $\mathcal{J} = \{1 \ldots 48\}$. We define $\chi := \{\{i, j\} \forall i \in \mathcal{I}, j \in \mathcal{J}\}$ and a tariff T as a partition over χ with $|T|$ *ToU blocks* T_b such that $\chi = \bigcup_{b \in \{1 \ldots |T|\}} T_b$. Every tariff T is uniquely determined by a partition over χ so we refer to both the tariff and the partition as T for brevity.

Although the flexibility of this set up is desirable, it leads to a large number of possible tariffs. As noted in [4], the number of partitions should not overwhelm customers. The authors note the differences between ToU pricing schemes and Dynamic (real-time) Pricing (DP). A weekday/weekend mechanism allows for separate prices to be applied on the weekend. A minimum block size ensures a price applies for a tangible period of time. The maximum number of blocks is specified for both $\mathcal{I}$ and $\mathcal{J}$. We enforce contiguous rectangular block structures on the ToU search space as follows:

(i) Redefine $\mathcal{I}$ as a set of week (or a weekday/weekend) blocks.

(ii) Partition $\mathcal{I}$ and $\mathcal{J}$ separately into contiguous blocks.

(iii) Combine the partitions of $\mathcal{I}$ and $\mathcal{J}$ into rectangular structures over χ.

The cent/kWh rate that applies for T_b can then be calculated as:

$$\hat{T}_b = \frac{\sum_{\{i,j\}\in T_b} H_{ij} f_{ij}}{\sum_{\{i,j\}\in T_b} f_{ij}} \tag{3}$$

3.2 Solution approach: Genetic Algorithm

Due to the nonconvexity and stochastic nature of the search space, a meta-heuristic approach was chosen to determine a tariff structure that minimises wholesale risk. A Genetic Algorithm (GA) with a bespoke representation of population individuals as well as custom crossover and mutation operators was developed using Python and the SciPy "ecosystem" of packages e.g., NumPy.

The genome is of variable length with three components: 1) the boundary points partitioning $\mathcal{I}$, 2) the boundary points partitioning $\mathcal{J}$ and 3) boolean variables showing the split between full week and weekend/weekday. The genotype is mapped to the phenotype through a function that takes the genome, H and f and produces a cent/kWh rate for each half hour. A function to create a random genome was written and used to initialize a population of random tariffs.

3.2.1 Crossover and Mutation

Crossover is performed by swapping, with uniform probability, the first, second or third components of two tariff representations. The remaining components are then adjusted to fit around the new component of both tariff representations. Mutation is performed by performing crossover of the genome to be mutated with a random genome.

3.2.2 Fitness Function - Simulation Model

The wholesale risk associated with each tariff T is determined by computing $Var(P(T))$, see Eq 1. This is the fitness of a tariff genome which is calculated using a simulation model of customer demand and outturn SMP, see figure 2. Recall both a_{ij} and S_{ij} are stochastic. Computational complexity is a key challenge when implementing this approach. The simulation model acts as the fitness function of the GA - for each member of a population (consisting of thousands of tariffs) a single simulation of wholesale risk must be performed. Each of these simulations themselves consist of thousands of simulations of both customer demand a_{ij} and SMP S_{ij}.

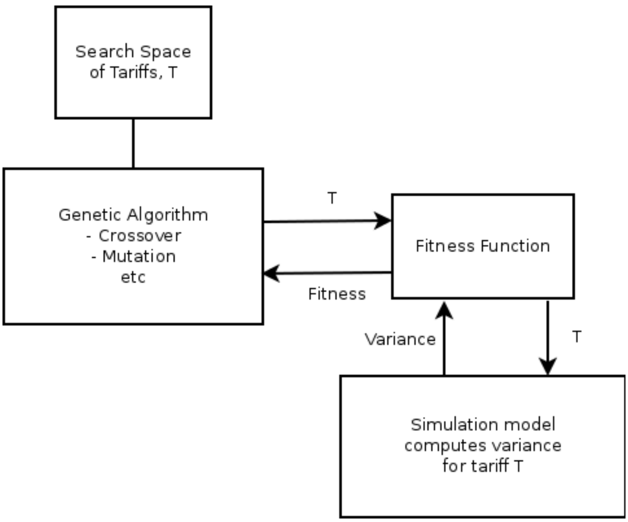

Fig. 2. The optimization approach: fitness function is a simulation model

3.2.3 Data - Demand and SMP distributions

The CER CBT data was used to model customer demand, [3]. Historical data for the SMP was taken from the SEMO website, [6]. As noted in [2] a *price volume correlation* is present in many electricity markets where higher system demand tends to imply a higher system price. The inclusion of such a phenomenon when modelling the SMP limits the data suitable for modelling to the intersection of the CBT demand and SMP data sets. Therefore the data between 14 July 2009 to 31 December 2010 were used.

Much work has been done to characterise electricity demand, see for example [5]. Models for both an inter and intra day basis were created for demand and SMP to capture the seasonal and diurnal patterns illustrated in figure 3.

A Fast Fourier Transform was applied to the inter day values to identify the frequencies of any seasonal behaviour. Based on the prominent frequencies dummy fourier variables were created and regressed against the daily data. The residual of this regression were then modelled using an ARIMA approach.

The intra day values were then modelled by first scaling the 48 values for each day. In the case of customer demand this was done by dividing

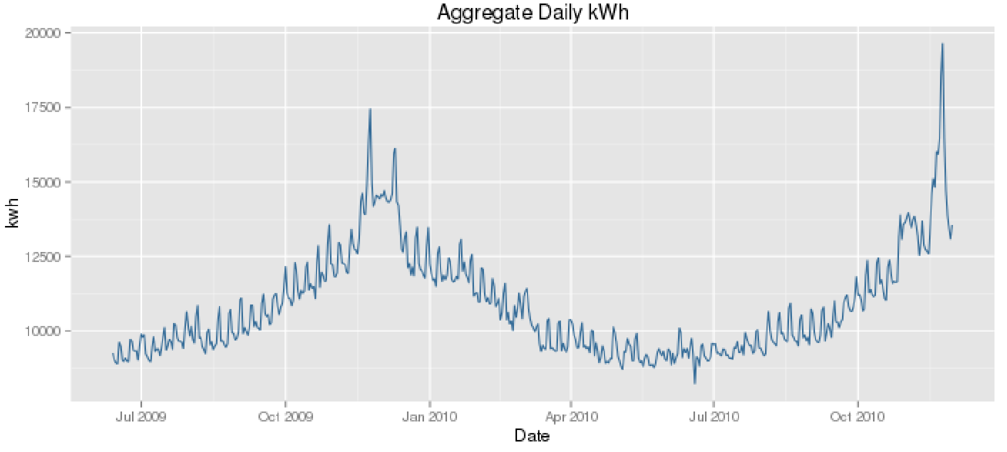

Fig. 3. Aggregated Customer Demand showing seasonal and diurnal patterns

each value by the sum of the demand in that day while for the SMP the average SMP price for the day was used. Note also that the price volume correlation mentioned previously is included through a simple regression of customer demand against the SMP. Each day was then treated as a vector in a vector space of 48 dimensions and principal component analysis used to reduce the dimensionality of the data sets. The first five components of the intra day data for customer demand explained 92% of the variance. For the SMP data, the first 5 components account for 49% of the variance.

Each principal component has an associated time series describing the presence of that component in the intra day shape for each day. These time series were modelled in a similar ARIMA fashion to the inter day data.

In order to reduce the computational complexity of the simulation model demand response was excluded from modelling. However the inclusion of same would be an important element of future work.

4 Results and Analysis

A portfolio of 10,000 customers was hypothesised with an average consumption of 4,200 kWh per customer per annum. The term of the tariff is 1st of October 2009 to 31st March 2010 i.e. 6 months or 182 days. The revenue associated with the energy component of the tariff (i.e. not transmission and distribution charges) from such a venture is circa €1,250,000.

Four separate configurations of the GA were run with a fixed generation

Configuration	Search Space Size	Minimum Found	Sq. Root of Minimum Found (€)	Average Minimum of Best Tariff	Sq. Root of Average Minimum (€)	Number of Partitions in best Tariff
1	147,355,998	3,656,041	1912	4,179,214	2,044	33
2	5,265,645	3,811,350	1952	4,349,316	2,085	25
3	2,713,260	3,774,253	1942	4,326,149	2,079	18
4	228,140	3,960,364	1990	4,439,781	2,106	15

Table 1
Summary of results.

size of 2,000 individuals. Each configuration varied the search space size by adjusting the min and max number of partitions. In each case it was found the results were dominated by a number of key features.

The resulting value of wholesale risk is itself a random variable since simulation was used. In every generation 2,000 simulations of equation 1 were performed when calculating the wholesale risk of each tariff. This gave a reasonable balance between the variance of calculated wholesale risk values and model run-time given the computational resources available. However the GA is always bias towards tariffs which experience an extreme calculation of wholesale risk and an increase in the number of simulations would be required to mitigate this effect. A summary of results can be seen in table 1.

The wholesale risk of a flat tariff (where one price applies at all times) was calculated to be circa €3,100. The results in each configuration are circa 30% less than this. Thus there would be a one third decrease in the risk to the supplier which may be reflected in a smaller risk premium being added to the tariff. The wholesale risk when compared to the total revenue of €1,250,000 is relatively small. However, it should be noted that residential electricity demand is predictable unlike the SME or Industrial and Commercial sectors.

The improvement in the average population fitness between early generations is evidence that a GA is an effective tool for exploring the search space. However, the generation fitness plateaus quite quickly causing the algorithm to stop within 15 generations in all configurations. Further configurations attempted to address this issue through refinement of parameters such as the tournament selection size and the generation size. There is scope for further exploration of the GA parameters, other configurations and increased processing power. We note that the valleys of the search space are very big, many tariffs may offer equivalent wholesale risk values and alternative optimisation techniques could be considered.

Furthermore, table 1 shows similar solution quality is obtained with tariffs that have a large number of ToU blocks and with those that have a small number. There is scope for the use of a fitness function incorporating a penalty of sorts based on tariff complexity. In particular, if the search space when considering wholesale risk alone is flat, this will provide a further avenue to differentiate between tariffs.

5 Conclusions

This work presents a novel concept in two respects. First it asks a question not covered by previous literature - can wholesale risk be reduced through the ToU configuration of a tariff? Second, a bespoke GA is presented with a custom representation, crossover function, mutation operator and stochastic fitness function.

It has demonstrated that there are ToU configurations that reduce wholesale risk. The reduction can be circa 30% when compared to a tariff with no ToU configuration based on the historical data modelled.

Given the likely flat landscape of the search space with tariffs of varying complexity giving similar results further work will explore the least complex tariff with the lowest value of wholesale risk by adding a penalty to the fitness function based on the complexity of the tariff.

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