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A Real-Time monthly DR Price system for the Smart Energy Grid

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Abstract

The smart grid is the next generation bidirectional modern grid. Energy users' are keen on reducing their bill and energy suppliers are also keen on reducing their industrial cost. Our demand response model would benefit them both. We have tested our model with the UK based traditional price value using a real-time basis. Energy users significantly reduced their bill and energy suppliers reduced their industrial cost due to load shifting. The Price Control Unit (PCU) and Price Suggestions Unit (PSU) utilise and embedded algorithms to vary price based upon demand. Our model makes suggestions based on energy threshold and makes use of stochastic approximation methods to produce prices. Our results shows that bill and peak load reductions benefit both the energy provider and users. This model also addresses users' preferences, if users are non-responsive, they can still reduce their bills.

Keywords: smart grid, real-time, price, demand response, stochastic process, user preference, peak to average ratio, price suggestion unit

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1. Introduction

Over the past few decades [1], technologies have experienced the development of a service model that makes our daily lives more convenient and comfortable. This is despite the fact that the population has doubled over the past century. This has, in turn, led to an exponential growth [2] in energy. Energy usages over the last 100 years has increased four-fold and researchers predict that automobiles, which are consuming energy, has led to a growth rate ten times faster than population growth. This growth is clearly unsustainable.

Currently, the power grid is a traditional grid that is used for electricity generation, transmission, distribution and control. It is unidirectional, transmitting power from generators to customers. Most developed countries developed their electricity grid more than 50 years ago, and it has become outdated. Using the current power grid, the USA could not avoid a major power cut in 2003, almost 50 million people were in without power for 2 days [3].

The Smart Grid (SG) is the ultimate solution to reducing the power load, decrease the carbon footprint and make the whole power network more reliable and secure. The SG is a bidirectional electricity network that can intelligently integrate the actions of all users connected to an energy grid in order to deliver electricity that is both sustainable and economically viable. There is [4] a vision by 2050 for energy appliances with downloadable energy from appliance manufacturers that nobody could have imagined in the 1980s. People will be able to pull energy from appliances with integrated virtual energy aggregators.

An energy supplier traditionally charges end users a flat rate, Time of Use (TOU) or Inclined Block Rate (IBR) basis. With that rate, energy users buy electricity on a peak and off-peak basis. An energy provider also buys their energy in that particular time with the high cost from the main power generation based on 'peakers'. In order to achieve the desired level of satisfaction, user preferences are important and it should be user friendly for the users so that they can choose their preferences in the Smart Grid to

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reduce their bill, however, energy provider concentrates on reducing the Peak to Average Ratio (PAR) on overall grid as their cost depends on that. Implementation of Real Time (RT) pricing addresses this issue. Energy providers maximise their profit by matching the demand from users on a RT basis.

We are currently facing challenges of global climate change, increasing carbon dioxide emission/greenhouse gas emission and an ever-increasing demand for electricity. We are very fortunate that we can face those challenges by using information technology. It would implement gradually without interrupting daily operation of energy with the current grid. Reliable operation is also challenging to get real time pricing. Pricing decision making is not straight forward due to how it has been taken into account for dynamic pricing- it can be in centralised or distributed - it appears to have the decision made locally or centrally.

Currently, the power grid's energy production has not been fully utilised, almost 70% of their energy is wasted [5]. There is a significant difference between average and peak demand. Energy providers must therefore produce energy to meet peak demand not average demand because of the unidirectional flow of energy. This thus leads to a significant challenge related to generating a system that can provide a balance between energy demand and supply.

Demand Response (DR) is being considered as a very effective and reliable solution [6] in the Smart Grid. Electricity price incentives are very useful tools to motivate customers to change their consumer behaviour within DR procedure and programs. It can be considered based on motivation offered to consumers within DR Schemes. Control mechanism motivators for consumers and the DR decision variable are the classification of the proposed scheme. Transition to energy efficiency is a key concept of the Smart Grid where volatile demands and renewable energy are concerned with the scalable information processing architecture [7]. DR is a subset of Demand Side Management (DSM) that manages customers demand and supply based on their time shape. Reducing the aggregate load in the distribution management system and taking real time [8] decisions can improve the reliability of the system [9]. In order to change the usage behaviour [10], DR systems can encourage customers to contribute to the program through incentives.

Considering motivation, customers are offered incentives and they are asked to respond to the system to shift their power demand in this DR approach. This could be based on time variance or incentive based. Offered incentives have a key impact on customer habits [11]. Incentive based Demand Response was studied in [12]. We have taken price control based DR mechanism into consideration.

The daily basis price suggestion presented [13], that considers the previous day only to calculate the price. This paper addresses the issue where energy users expect their monthly bill based on their monthly usages though monthly basis data dimension is significantly high. The Pricing algorithm works on a monthly basis and reductions are made based on the previous month's usage. The remainder of the paper is structured as follows, Section II discusses the available pricing methods, Section III discusses the concept of price suggestions, Section IV discusses the results obtained in our model and finally Section V presents the main conclusions.

2. Discussion of pricing methods

Different types of pricing methods [6] are found in different research especially on flat price, Time of Use (TOU), Inclined Block Rate (IBR), different types of peak pricing such as Critical Peak Pricing (CPP), Variable Peak Pricing (VPP), Peak Load Pricing (PLP), Day Ahead Real Time Price (DA-RTP) and Real Time Price (RTP) basis. However, time varying prices are involved with incentive based programmes. TOU is the application of flat pricing, it is a traditional energy pricing system and it has been the most commonly known approach for some time. There are hours identified by energy providers as peak, mid peak, off peak etc. based on aggregate consumptions and each group has different rates in TOU. Based on this maximum demand Peak Pricing (PP) has been used by many utilities companies for large industrial loads. The aggregate of the peak, off peak or mid peak load are considered.

A Consumer's monthly, daily, or hourly load beyond a threshold are considered in Inclining Block Rates (IBR) [14] and based on consumption the price increases to a higher value if it exceeded the marginal price. This influences consumers to keep their load below a certain level at certain times. In Washington, DC, Pepco's customers reduced their bills by 20% using a Critical Peak Pricing (CPP) program in the summer. Many utilities take Day-Ahead-Pricing into account and it (DAPs) can be calculated based on the clearing market prices and carry a separate price for each hour of the next day in the day-ahead market. Day-Ahead RTP (DA-RTP) is an alternative solution for RTP. Customers know their predictive price in the next day.

RTP pricing has been practised by the Electric Reliability Council of Texas [15] for consumers. These prices are updated every 15 minutes (not a real time basis). RTPs are calculated only after-the-fact, and this can create uncertainties for consumers. RTP has been implemented before and the challenge is real time communication between the energy provider and users. However, without taking a users' responses into consideration high customer satisfaction is not possible. There is an RTP pricing algorithm [16] proposed in the digital based Smart Grid as it is an assumption that customers are using an Energy

Consumption Scheduling (ECS) device. This research focuses on RTP as people aspire ease and an instant decision making system. RTP is proposed for different customer types, e.g. Residential, commercial, and industrial.

This paper addresses the issue of traditional price that is sometimes unfair for energy customers. This model will give an overview of the customers' monthly bill savings. An Energy supplier would benefit from the model as peak load would be reduced through the model. Monthly basis energy customers complained that they are sometimes overcharged as the traditional grid is unidirectional. The model depends on customers' meter reading input or they are producing the estimated billing. Smart Grid is a solution which is bidirectional and the proposed model would collect data from the smart meter and present it to two devices i) a price suggestion unit and ii) a price control unit. Customers respond to the demand response price suggestions for their benefits. However, it would be a challenging to get a response from them. Price suggestions made based on individual energy consumptions, price control unit takes the consumptions and calculate the prices if any user non responsive still they benefit from the model. At the end of the month once they see the reduced bill it would be encouraging for them to engage with the system more and more.

This paper aim is to minimize an energy users' bill and the energy provider's profit based on users' demand, as they would receive information on a real time basis. The energy supplier would set their price based on users' demand and their industrial marginal cost. In order to minimize the Peak-to-Average Ratio (PAR) in the load demand through pricing, users need to respond, but it is difficult to get response from users, some of the users respond some of them do not. This paper addresses the issue of user non-interaction and uncertainty that was not considered in [17] users' price- responsiveness. A User sometimes does not respond because of a lack of awareness [18].

This research is aimed at developing a real time optimised Demand Response pricing model, especially in the users' demand side of the smart energy grid. This new proposed pricing algorithm addresses those issues above, particularly addressing users' choice without interrupting their energy preferences. Besides this, this model is able to reduce consumers' bills in accordance with their consumption and that would assist the energy provider to take decisions about real time prices. Moreover, it would maximize power system reliability, change the demand to follow the supply with high penetration of renewable energy especially solar and wind as energy providers have an obligation to address pollution levels. It would also ensure the benefits for all categories of customers and accommodate users' aspired electricity pricing on their usages, simplify the nature of data complexity and maximize social welfare and maintaining system stability with minimum curtailment.

Our model addresses the energy supplier who are eager to minimize the Peak-to-Average Ratio (PAR) in aggregate load demand and energy consumer who also eager to receive an optimized price on a Real Time basis. It also addresses the challenge of the uncertain impact on a users' profile depending on the energy provider's price selection.

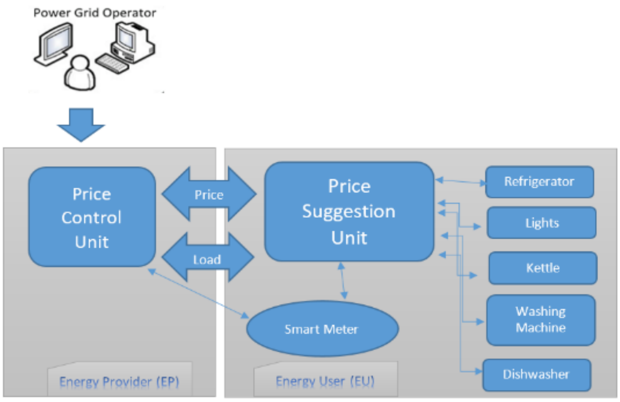

Figure 1. The architectural diagram of the model.

In the Fig. 1, algorithm works in the price control unit that resides in the energy provider side and also algorithm works in the price suggestions unit that resides in the energy consumer side. In the Smart Grid, we assume that users will be equipped with a Price Suggestion Unit (PSU) and the energy provider will be controlling price with their price control unit by communicating with a customer's smart meter. We tested the model with the UK based University and Department for Education based upon a pre-existing data set (30 days half-hourly basis 14 buildings). We produced a result where we have shown that each building benefits from the proposed system. Data has been recorded from a smart meter that is connected to all other appliances.

On the user side, the price suggestion unit would be connected that also should be connected to their smart meter. In the energy suppliers' side, a price control unit would be connected; we developed an algorithm in the price suggestion unit and another algorithm developed in the price control unit. The price suggestion unit would offer the customers an opportunity to respond; however, if users are non-responsive, still they would reduce their cost because of taking advantage of the responses from others. Our algorithm was formed based on stochastic methods [19]. A previous study shows [12] incentive might be helpful in increasing response rates, however, we have tested even with a 20% response rate and we have received significant results. The results show that peak load is significantly reduced. Customers received lower bills than those of traditional pricing methods. The price was calculated based on a real time basis minimum, maximum and threshold basis. This process is stochastic, therefore noise and loss function have been minimised with simultaneous stochastic process.

The proposed model will automatically optimize consumers' demand. If someone wants to save more on their bill they have to respond to the energy providers' price suggestion. The algorithm can handle price objective functions, ignoring the customers input. However, customers are not required to respond, they will receive an optimised price, if someone wants an additional reduction from their bill than they can interact with the Price Suggestion Unit (PSU), and accordingly set their appliances which will lead to further price reductions and an optimised price value. This approach will ensure that both types of customers will benefit from the system.

This model takes input from both types of customers. It can handle malicious responses of the customers, for example in the large amount sample of data this algorithm would able to minimise the loss function where the missing data or misjudged data can be received by the system from users. As there is the option of receiving a customer response that will handle both automated and manual input in the system to make the decision. A stochastic process is implied in the PCU, which minimises its loss of data and will still provide an efficient optimised price.

User input is significant for the energy provider, but some of the users don't respond as they want comfort, and are not interested in reducing the price. The user's response is being taken into consideration for different price values. The PSU on a user's profile is important which is achieved by using that unit. The stochastic approach is considered from customers' demand side on a real time basis of this proposed model. Details of usage or customer's intentions are used as part of scheduling by the PSU. This algorithm addresses both customers who are very keen on savings and customers who are not interested to save on their energy bill. Indeed, in the future, it is assumed that every user will be equipped with PSU units along with their smart meter. The Price Suggestion Unit (PSU) will dynamically collect a users' choice based on the price imposed by the energy provider. If users' aspire to reduce their price more, they will respond the Price Suggestion Unit (PSU) otherwise the Price Control Unit (PCU) will calculate the optimized price value for the customers without counting their response. Both options are available for consumers because some consumers don't like schedule change by interrupting their comfort, but other users' do wish to reduce their price value by responding to the suggestion unit.

3. Price Suggestion Unit

A Price Suggestion Unit (PSU) is connected to a smart meter that connects to all appliances. The smart meter collects all Half-Hourly energy consumptions real-time data that pass on to PSU which make suggestions for the users' based on one-day (48 half-hourly slots) data.

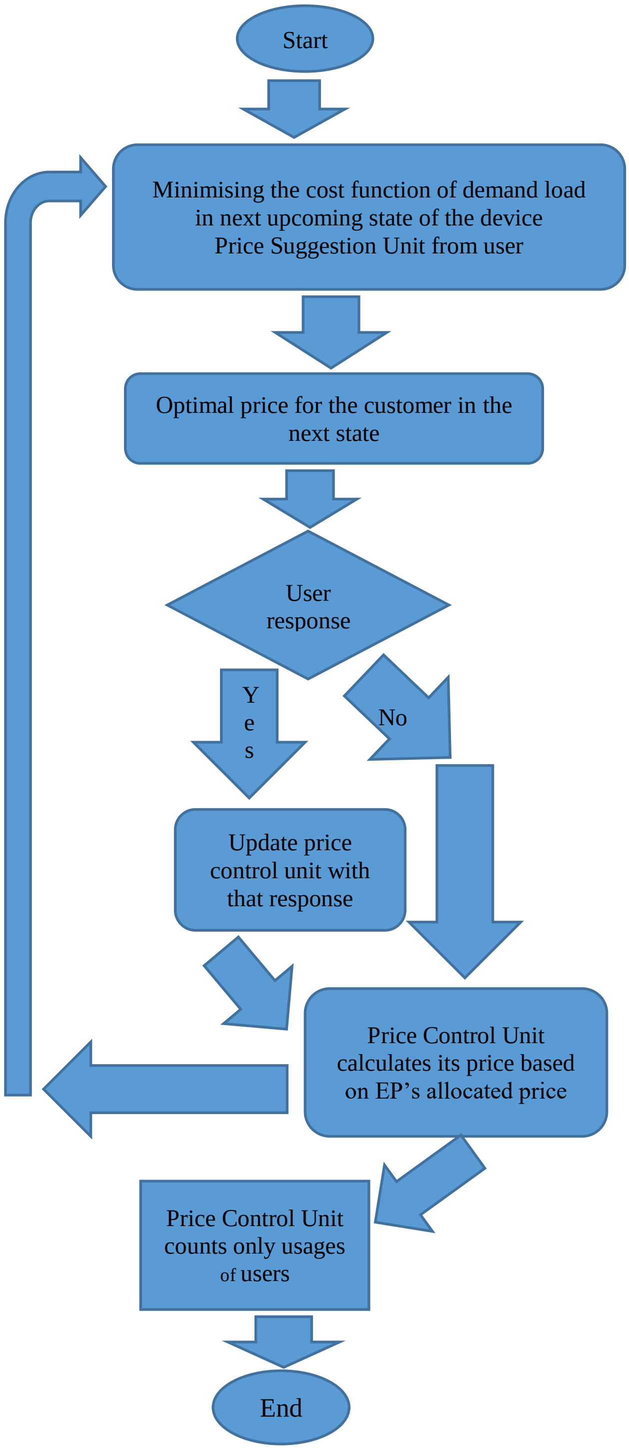

Figure 2. Proposed pricing model working procedure

The more data stored the more accurate suggestions made based on historical data. This unit suggests based on threshold consumption of the user load. The algorithm finds the lowest possible load, and makes suggestions for the particular energy users' balancing the particular time slot of the whole Smart Grid (SG). The PSU would expect a response from the user, however, if the user is non-responsive, energy consumption would still be passed on to Price Control Unit (PCU) and stochastic price approximation algorithm calculates the price on a real-time basis and generates the price signals to the users. The stochastic method would handle the loss and noise function.

The model [13] (modified)_ is shown in fig. 2 where minimising the cost function of demand load in the next upcoming state of the PSU from a user and algorithm developed in PSU would assist to reduce the peak load. User response would benefit energy suppliers to reduce 'peakers' and, ultimately, industrial cost. The PCU calculates price based on a users' final consumption. Users' would be attracted to respond to the system for the achievement of greater benefit for users and, ultimately, for the whole SG. Our model generates the prices based on 48 time slots and it optimises the user monthly bill as model takes individual consumptions into consideration. Every user benefits from this real-time based price generated model and essentially reduces their bill. Peak load has been reduced significantly through the PSU. Final consumption would update the PCU to produce final monthly bills for every individual user.

We denote the users' building B as $b_1, b_2 \ldots\ldots\ldots\ldots\ldots b_m$, day as d that defines as $d_1, d_2, \ldots . d_q$, where every day is being divided l number of timeslots of the time T as t_1, $t_2 \ldots\ldots\ldots\ldots t_l$ where $t \in T$, $b \in B$ and we can have the matrix as

$$\begin{array}{l} b_1 d_1 t_1 \ldots\ldots\ldots\ldots b_1 d_1 t_l \\ b_2 d_2 t_1 \ldots\ldots\ldots\ldots b_2 d_2 t_l \\ . \\ . \\ b_m d_q t_1 \ldots\ldots b_m d_q t_l \end{array} \qquad (1)$$

Producing a summary matrix in each independent building user for the time slots

$$\begin{array}{l} b_1 d_1 \sum_{l=1}^{48} t_l \\ . \\ . \\ b_m d_q \sum_{l=1}^{48} t_l \end{array} \qquad (2)$$

Where $l = 1,2 \ldots\ldots 48$, $m = 1,2, \ldots . n$, $q = 1,2, \ldots 30$

Defining the summary matrix as

$$[\sum_{m=1}^{n} b_m\, d_1 t_1 \ \ldots\ldots\ldots\ldots \ \sum_{m=1}^{n} b_m\, d_q t_{48}\,] \qquad (3)$$

Average over a month matrix as

$$\begin{array}{l} \frac{\sum_{m=1}^{n}\sum_{q=1}^{30}\sum_{l=1}^{48} b_m d_q t_l}{30x48} = a_1 \\ . \\ . \\ \frac{\sum_{m=1}^{n}\sum_{q=1}^{30}\sum_{l=1}^{48} b_m d_q t_l}{30x48} = a_m \end{array} \qquad (4)$$

Every time slot produces an average matrix as

$$[\frac{\sum_{m=1}^{n} b_m\, d_1\, t_1}{n} \ldots\ldots\ldots \frac{\sum_{m=1}^{n} b_m\, d_q t_{48}}{n}] \qquad (5)$$

Overall building basis average = $\frac{\sum_{m=1}^{n}\sum_{q=1}^{30}\sum_{l=1}^{48} b_m d_q t_l}{n}$ (6)

Every office building produces a surplus matrix as

$$\begin{array}{l} b_1\, d_1 \sum_{l=1}^{48} t_l - \sum_{l=1}^{48} a_{1l} \\ . \\ . \\ b_n\, d_q \sum_{l=1}^{48} t_l - \sum_{l=1}^{48} a_{ml} \end{array} \qquad (7)$$

Producing a change position matrix from first matrix as

$$\begin{array}{l} (b_1\, d_1 t_1)_{ch}\ (b_1\, d_1 t_2)_{ch} \ldots\ldots\ldots (b_1\, d_1 t_{48})_{ch} \\ . \\ . \\ (b_m\, d_q t_1)_{ch}\ (b_1\, d_q t_2)_{ch} \ldots (b_m\, d_q t_{48})_{ch} \end{array} \qquad (8)$$

Where
$(b_1\, d_1 t_1)_{ch} = b_1\, d_1 t_1 - a_1$, $(b_1\, d_1 t_2)_{ch} = b_1\, d_1 t_2 - a_1$ .. $(b_1\, d_1 t_{48})_{ch} = b_1\, d_1 t_{48} - a_1$ Subject to $b_1\, d_1 t_l > a_1$
.
.
$(b_m\, d_q t_{48})_{ch} = (b_m\, d_q t_{48}) - a_m$, $(b_m\, d_q t_2)_{ch} = (b_m\, d_q t_2) - a_m$.. $(b_m\, d_q t_{48})_{ch} = b_m\, d_q t_{48} - a_m$ (9)

Subject to $b_m\, d_q t_l > a_m$

The sum total of the each user time slots defined as

$$= d_q t_l \sum_{m=1}^{n} b_m \qquad (10)$$

where $l = 1,2 \ldots\ldots 48$, $m = 1,2, \ldots . n$, $q = 1,2, \ldots 30$

The total sum of energy usages in each time slot

$$= b_m d_q \sum_{l=1}^{48} t_l \qquad (11)$$

where $l = 1,2 \ldots\ldots 48$, $m = 1,2, \ldots . n$, $q = 1,2, \ldots 30$

Every user threshold load calculated as

$$= \frac{d_q t_l \sum_{m=1}^{n} b_m}{m} \qquad (12)$$

Every time slot-threshold load defined as

$$= \frac{b_m d_q \sum_{l=1}^{48} t_l}{30x48} \qquad (13)$$

Considering each user threshold load, the algorithm checks the lowest possible load from all users without exceeding the threshold load in each time slot of the whole grid. Suggestions made through the algorithm are implemented in th PSU. From the pricing algorithm, a user can receive an optimised price value but it is based on current usage of electricity. However, the energy provider might update the price value based on demand and industry running cost. Users would receive suggestions based on the selected price value of the energy provider. Every half-hour, based on total load, the energy provider updates p_t. Accordingly min_t max_t can be updated. The energy provider selects p_t based on total load and the total running cost of the industry.

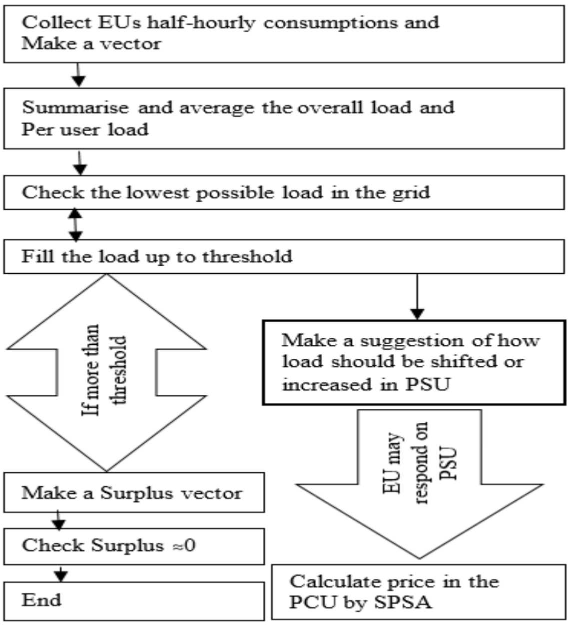

Figure 3. Proposed pricing model working procedure

Collect user responses and the suggestion displays in the price suggestion unit for the users who need to follow the suggestions to save money on their bill. This algorithm is able to reduce the peak to average ratio from the energy provider point of view at the same time users' response counts and calculate their prices in real time basis. In this algorithm, we simulate the user response for example 20% of the suggestions they follow. We measured their response and produced a result that shows peak to average is being reduced and users' save their bill compared to flat rate pricing solution.

Users' equipped with a smart meter and Energy supplier communicate their price by using a Local Area Network. The Price Suggestion Unit informs user's optimal usage plan and their actual usages so that they can be aware of what they are approaching to spend. An energy user may use IoT enable devices so that PSU unit and smart meter can collect data using a sensor.

4. Problem formulation in PCU

Let us define an office user based total power load $L_b^t \triangleq \sum_{a \in A} l_{a_{u_t}}$, the algorithm proposed in [13] and assume that there will be a maximum or minimum charge applied based on the office usages. Let us denote min_t max_t thr_t as the price parameters, which can be defined as

$$p_t(L_b^t) = \begin{cases} min_t, & if\ 0 \le L_b^t \le thr_t \\ max_t, & if\ L_b^t > thr_t \end{cases} \tag{14}$$

Where thr_t is threshold price parameter; it can be selected by the energy provider. Offices' usual energy consumption for example 40 kWh in a particular half-hourly time slot. The total day has been divided into 48 time slots, on a half hourly basis that is defined as T, where $t \in T$, and $T = t_1$, $t_2, \dots \dots . t_{48}$.

In order to reduce the Peak to Average (PAR) of aggregate load, define $P_t \triangleq (min_t\ max_t\ thr_t)$ is a vector of the total set of price vector $\mathrm{P} = (\mathrm{P}_1, \dots \dots \dots . . \mathrm{P}_T)$. The price of the electricity depends on total half hourly basis energy consumption and buildings denote as $B = b_1$, $b_2 \dots\dots b_n$, $b \in B$. Energy supplier deciding price is p_t at time t. Considering RTP half hourly basis optimised price value for the clients, we defined

$$\underset{\mathrm{P}}{minimise}\ \phi(\mathrm{P})$$

$$\text{Subject to}\quad \begin{aligned} & min_t^{min} \le min_t \le min_t^{max}, \forall t \in T \\ & max_t^{min} \le max_t \le max_t^{max}, \forall t \in T \\ & thr_t^{min} \le thr_t \le thr_t^{max}, \forall t \in T \\ & min_t \le max_t, \forall t \in T \end{aligned}$$

$$\text{Where } \phi(P) = \max \{L_1(P) \dots\dots . L_T(P)\} \tag{15}$$

There are three elements in the price objective function $\phi(P)$. Those are maximum, minimum and threshold prices based on threshold load. All price parameters are calculated by multiplying the price parameter p_t. If an office user exceeds the limit in that particular time slot, then they will be charged the maximum range of price, otherwise the minimum range of price would be charged all the way of their usages.

In order to measure our objective function, every pricing element change in the vector P, and the jth element of vector P is perturbed. This vector would be measured through the iterative process and the ratio of change of objective function for perturbation of the jth element of gradient vector of $\phi(P)$. The price parameter P can be perturbed through this equation

$$\mathrm{P}^{i+1} = \mathrm{P}^i - \sigma^i\, \hat{g}^{\,i}(\mathrm{P}^i) \tag{16}$$

Where $\hat{g}^{\,i}(\mathrm{P}^i)$ is an estimated gradient vector of $\phi(\mathrm{P})$, in the i times iterative process, P^i would be input vector. Its step size would be $\sigma^i > 0$ that can be reduced when the number of iterations increased to make it convergent. The dimension of the vector would be K = 3T or T. Where ε_j position would be 1 and the rest of the positions would be zeros and coefficient $c^i > 0$ would be the magnitude of perturbation. In accordance with J, spall suggestions [19], we can select σ^i and c^i in the form of

$$\sigma^i = \frac{\sigma}{i+1+A^{\alpha}},\ c^i = \frac{c}{(i+1)^{\gamma}} \tag{18}$$

Where $\alpha, \sigma, \gamma\ and\ c > 0\ and\ A \geq 0$ would be for the improvement of convergence of this algorithm.

The way of gradient approximation would be a simultaneous perturbation stochastic approximation. In that method, the algorithm jointly and randomly perturbs all elements of P^i. In the state of objective function ϕ (P^i), it can achieve two different types of perturbed measurements and that can be written as

$$\hat{g}^{\,i}(\mathrm{P}^i) = \begin{bmatrix} \frac{\phi\,(\mathrm{P}^i + c^i\varepsilon^i) - \phi\,(\mathrm{P}^i - c^i\varepsilon^i)}{2c^i\varepsilon_1^i} \\ \vdots \\ \frac{\phi\,(\mathrm{P}^i + c^i\varepsilon^i) - \phi\,(\mathrm{P}^i - c^i\varepsilon^i)}{2c^i\varepsilon_{\mathrm{K}}^i} \end{bmatrix}$$

$$= \frac{\phi\,(\mathrm{P}^i + c^i\varepsilon^i) - \phi\,(\mathrm{P}^i - c^i\varepsilon^i)}{2c^i} \left(\frac{1}{\varepsilon_1^i}, \ldots\ldots \varepsilon_{\mathrm{K}}^i\right) \tag{19}$$

Where $\varepsilon^i \triangleq (\varepsilon_1^i, \ldots \ldots \ldots \ldots \varepsilon_{\mathrm{K}}^i)$ is the perturbation vector and $\varepsilon_j^i \in \{-1, 1\}$ is a random number. In every iteration, we will have two measurements and the size of the vector would be $1 \times \mathrm{K}$. If the size of the vector is large, simultaneous perturbation stochastic approximation is effective in terms of the finite difference technique. Two measurements complexity might be beneficial as fewer iterations would be required to achieve an optimised value of P^*. We propose an algorithm, which can be executed within the price control unit (PCU). We commence the algorithm with an initial value of $\alpha, \sigma, \gamma, \mathrm{P}^0\ and\ A$. At the i^{th} iteration, we update the values in the equation number (18) and then we update the values in (19) and accordingly P^i is updated based in (16). In case of maximum number of iterations, the algorithm terminates. Difference between two successive values of the objective function is less than a predetermined threshold would stop the algorithm. Where ϵ^i represents observation noise or bias term according to Y, He, [20] the conditions of the convergence met.

As this is multivariate analysis, it is not possible to fully analyse and understand some of stochastic algorithms without advance mathematics. Modelling is trying to find an optimum objective price function that would benefit clients and energy provider as well as welfare for the society. In order to gain the outcome of the function, we have used the Simultaneous Perturbation Stochastic Approximation (SPSA) optimization technique [21]. Search and optimization techniques would provide the way of taking the best decisions in the problem. Finding out vector P that minimizes a scalar value loss function L (P) by solving the equation g (P) =0. In a stochastic gradient framework, direct, unbiased measurement of gradient g (P) = derivatives of P is used in the Stochastic Approximation (SA) algorithm.

This method is useful in the case of direct measurement failure of gradient function g (P) with diverse values of P. For a multivariate system, Simultaneous Perturbation Stochastic Approximation (SPSA) is useful. It also works in stochastic gradient or gradient-free scenarios. In order to gain precision, it assists to reduce loss dimension during the process. This SPSA works better in the stochastic environment with the availability of loss measurement and it is based on Y (P) =L (P) +E at various values of P, where E is noise function.

In order to reduce the number of measurements in high-dimensional problems SPSA is especially efficient in terms of providing a good solution. We used the convex convergence technique where general norms of convergence function that can be three times differentiable, but Ying et al [20] omitted differentiability requirement and developed convergence using convex analysis. Gradient approximation in SPSA would be achieved by perturbing the elements one at a time. Accumulation of loss measurement y (P) at each of the perturbation, all elements are randomly perturbed together to obtain two loss measurements of y (P). For two sided SP gradient approximation. Where the mean-zero p dimensional random perturbation vector has a user specified distribution satisfying conditions and c_i >0 is positive scalar. Because numerator is the same in all p components of $g^i(P)$. Number of loss measurements needed to estimate the gradient in SPSA are two, regardless of dimension of p. Whatever situation of users or energy provider side probabilistic nature of the data can handle properly by a stochastic process [19].

Simultaneous Perturbation Stochastic Approximation (SPSA) has been successfully applied to many optimization problems such as industrial quality improvement, pattern recognition, queuing systems, simulation-based optimization with air traffic management and military planning, aircraft design, bio process control, neural network training, chemical process control, fault detection, human-machine interaction, sensor placement and configuration, and vehicle traffic management. It is the process of calculation of random probabilistic data even not only in the loss incurred situation but also in noisy environment.

5. Results

We have calculated the overall Peak to Average Ratio (PAR) based on total load (of all buildings) from energy provider point of view. Energy Provider (EP) would think about total load demand from energy users. Nonetheless, whatever demand in particular time slot out of 48 slots, Energy supplier supplies the same amount of energy to meet the demand of Energy consumers. In order to meet the users' peak demand, the Energy supplier supplies the maximum amount of energy. We calculated what would be ratio of peak demand and total load as the PAR. We also calculated building based PAR, so that we know individual buildings PAR. Based on overall average energy consumption, we assume that at least we could bring down peak load to average load. We define it as target PAR.

However, we also calculated the flat rate price, it shows users costs are influenced by the peak energy consumption that is being found that can be suggested to reduce to average consumption, i.e. users' would shift their load from a particular peak time slot to another slot. Real Time (RT) prices have been calculated by using simultaneous perturbation stochastic approximation method that reduced users' bill significantly. The graphical representation shows that the overall demand from users is 32588 kWh. However, average consumption is per time slot is 678.9 kWh where peak demand is 1073.5 kWh and minimum demand is 322.3 kWh. We generated different graphical representations for each different buildings load where it shows that in Sanctuary buildings (sample), 426.56 kWh is the average load, its peak load 691 kWh, lowest load is 174 kWh. Total load in Sanctuary buildings is 20475 kWh.

The volume of different buildings' energy usages clearly shows in the graphs that sanctuary (sample) is large building where electricity consumption is high from 8am to 8pm. They used energy mostly in the launch time. We found that these are department of education buildings people mostly usages their electricity during their office times. However, average users demand per time slot is 678.9 kWh where peak demand is 1073.5 kWh and minimum demand is 322.3 kWh.

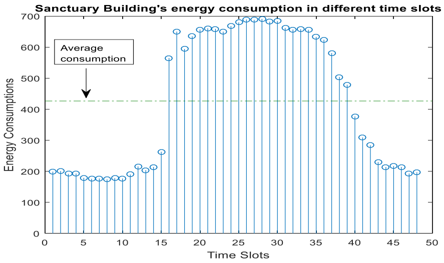

Figure 4. Energy load distribution in Sanctuary building (sample)

In Sanctuary building, graphical representation shows that load pattern base price charged in different slots, no variation. However, RT pricing varies in different slots which we have shown in the previous graph. They mostly use their energy from 7.30am to 4pm. Real Time pricing should be dynamic. An Energy Provider's decision on price selection would impact on user profile. We use around flat rate random price, but in a dynamic way to charge on user profile in every half-hourly basis. Energy provider can set their price maximum, minimum based on threshold load on user profile.

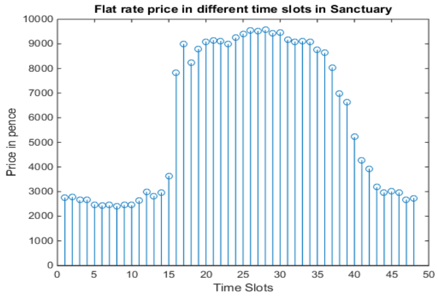

Figure 5. Flat rate pricing in Sanctuary building (sample)

The graphical representation shows how those minimum, maximum based on threshold load in different buildings. Overall pricing is also implied on the price parameter, but because of data variability, price implied in individual building has obtained significant result. The graphical representation of the fig. 6 shows how the Sanctuary building is being charged lower average and high price. In order to determine the best price practice, real time basis generation and distribution cost should be exposed in pricing. Vibrant, real time pricing benefits the Smart Grid. The vital question is whether real cost is reflected by purging appropriations. Some of the research shows that the time of use pricing may reduce peak demand; technology might assist to achieve this.

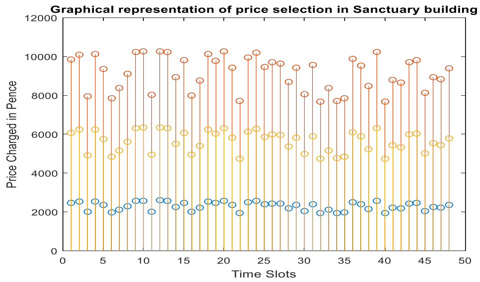

Figure 6. Maximum, minimum charged in Sanctuary building for real time price calculation

In the scenario of deployment of smart grid, customers' needs to act smartly to respond the price signals. Energy Providers demand response programme itself assist to reduce one third of half of total benefits in the deployment of smart grid even with flat rate pricing. In the flat rate pricing, some of the users might be over charged or under charged while they are responding on time of use basis flat rate pricing on incentives - this will not influence users to shift their load. However, real time pricing is the solution for them as there will not be a question of over or under charging for their usages. Real Time pricing is based on generation, transmission and distribution cost. There is some risk involved in that scenario that users might not be able to reduce load in the peak time, so still risk incurred. Therefore, we should take middle approach that real time pricing and release pricing policies that introduce effective communication to users about the price changes. In Sanctuary building, there are time slots like 7.30am, 10am, 10.30am, 1pm, 3.30pm and

7.30pm are charged, highly, and we could suggest that if they can shift their load from those slots to off peak time that would reduce their bill significantly.

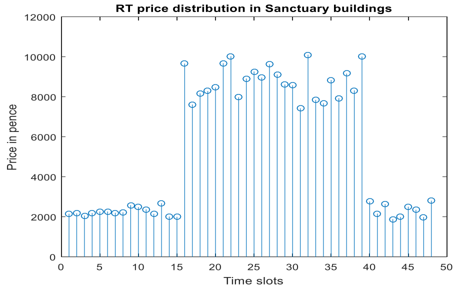

Figure 7. Real time pricing in Sanctuary buildings in SPSA

The graphical representation shows most of the time slots for the Sanctuary building has led to an increased price in real time basis from flat rate price. In time slot number 39, 7pm, it significantly lost because of its disproportionate load profile. We would suggest users if they can shift their load from the time slots they lost their price to off peak position that would help to reduce the PAR.

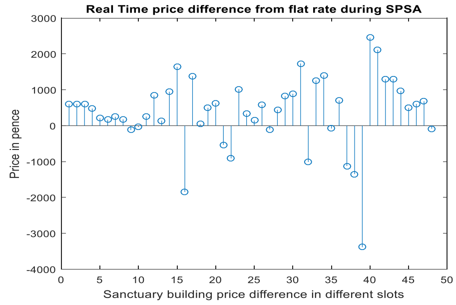

Figure 8. Price difference in Sanctuary Building from flat rate in different slots

Again, we have also used 10 building users' energy consumption data that collected from the University of Bedfordshire. Their data includes half-hour energy usages that collected through smart meter. Monthly data used to show the reduction, however, day wise suggestions made and users' need to respond time slot wise. Graphical representation shows the reduction load through downward bars and increased load through the upward bars. Algorithm produced real-time price that based on particular user's threshold load. If user exceeds its threshold then it would charge maximum rate otherwise minimum rate. We counts 20% response in the suggestions unit only based on several research [22]. Given example of the one building shows that where to shift their energy, like one users' enrgy usages lies between 7am to 4.30pm. PSU would show it's average consumption 400kWh and where to shift it's energy. Energy users' monthly bill has been significantly even without responses to price suggestions unit. Without shifting their load they can save their price in terms of traditional price value. After load shifting they can save more. Energy suppliers are charged by main power grid based on peak load. Peak load reduction benefit the energy suppliers.

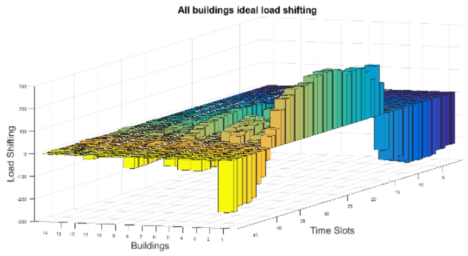

Figure 9. At a glance load shift suggestions per building per time slot

If all of energy suppliers use this algorithm then overall smart grid would produce less energy than the existing supply. All of the graphical representation shows that price reduction in terms of users. In an average per day peak demand reduced almost 129 kWh, from 1716 kWh to 1587 kWh. Users' monthly basis saved their bill significantly that is almost 3870 kWh.

Figure 10. Users' monthly price reduction (Standardised) in terms of flat rate

Our model shows that energy users' significantly reduced their monthly energy bill using real-time pricing. This graphical representation shows that every building reduced their bill. Considering traditional price value per unit energy consumption, we have checked how much money users are spending with real-time basis price at the end of the month. Users' are better off with this model. Most importantly, energy suppliers are not losing their money, but the challenge is that energy suppliers' cost currently depend on 'peakers'.

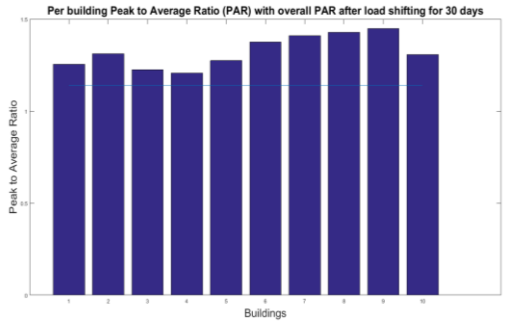

Figure 11. User based PAR with overall PAR after monthly load shifting

Peak load leads to their industrial cost. This model also addresses that issue. Fig. 11. Shows that this model can assist in reducing the peak to average ratio from 1.5 to 1.2.

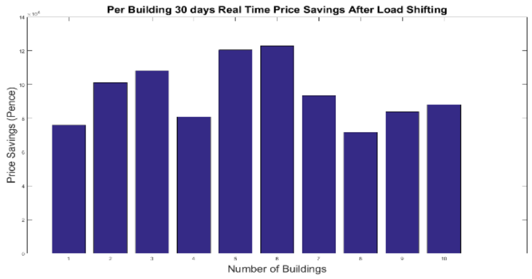

Figure 12. Monthly real-time price reduction in terms of traditional price after load shifting.

The energy suppliers are better off in terms of buying the energy from the power plant. If all energy suppliers are using this model, after all power plant do not need to generate much energy to meet the users' electricity demand. Fig. 13. Shows that total monthly basis energy load in each time slot, it shows that which time slot would most significant to address. Peak load shows in the middle that is the most significant load incur cost of the energy suppliers.

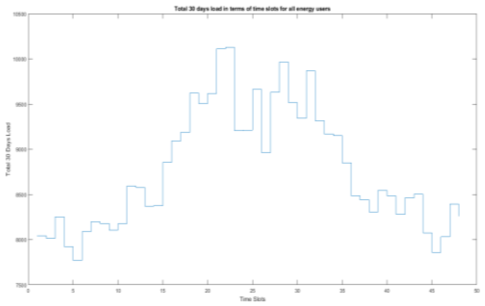

Figure 13. Total monthly energy load in each time slot

Similarly 3D fig. 14 shows at a glance users' usages. Time slots are on the X-axis, Users' are on the Y-axis, energy load on the Z-axis to understand at a glance the current scenario of the energy load occurs in the grid.

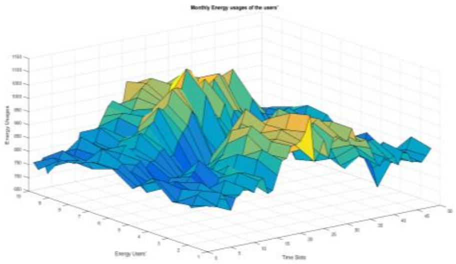

Figure 14. Monthly energy usages of the users'

Fig. 15 shows that how energy in which time slot users need shift based on suggestions. PSU suggests that how energy, users' should shift and where. Ideal suggestions made for the users', however, model does not expect everyone's response. It shows that energy providers and users both are better off with this model. It also shows the suggestions based on threshold load, sample one building suggestions shows where to energy shift and yellow upward bars show that users' need to reduce the energy usages and downward bars show that users' can increase the energy usages. We collected data from open sources online based portal of department of education [23] in the UK and University of Bedfordshire. We search in different govt. office data that are half hourly basis accumulated appliances data in different slots.

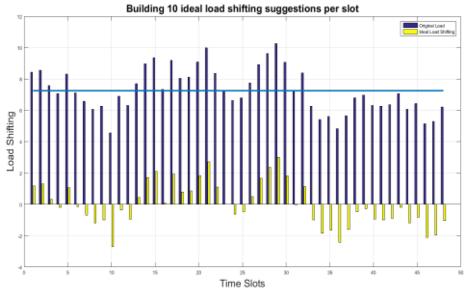

Figure 15. One users' (example) load shifting suggestions per time slot

Different company charges in different rate however, they are charging almost similar flat rate basis. For example, Utility warehouse is charging 13.844 pence per kWh. The buildings of DfE in the UK shows that they have 24 hours energy consumption in their places. This research result is being produced by using MATLAB 2015 (b). This tool has been used for developing the algorithm.

6. Conclusion

We have considered a model based upon 48 half-hourly slots to identify energy consumption. Our model shows that Real Time monthly based Price is better than Flat rate pricing. We have found the time slots that can be suggested to users and manage their load more effectively and reduce their Peak to Average Ratio (PAR) through use of a Price Suggestion Unit (PSU). A Real Time Price (RTP) based Demand Response model was developed by considering users' preferences by using stochastic optimisation techniques. Considering variable pricing constraints from both renewable and non-renewable, our proposed real-time pricing algorithm will solve the issue for the future Smart Grid. Users load pattern and their preferences were considered when designing this algorithm. Moreover, it collects information from a local distributed system and manages users and energy providers automatically. It would find users optimal consumption to reduce the aggregate load. It would also make production cost low for energy providers to satisfy the consumers' demand.

A Half-hourly measurement is recorded in the entire time cycle of 48 half hour time slots. Power requirements might vary in each slot. By considering Real Time Pricing (RTP), user responses designing a Demand Response model is a complex problem. The proposed model addresses the issue of efficiency and cost effectiveness to implement a Demand Response model in the future Smart Grid. To ensure real time communication between users and energy providers, robust, a secure and reliable communication infrastructure is important for implementing Demand Response programs in the future Smart Grid and that can change the future direction of the research to support this proposed model.

Use of multiple sources would be integrated to yield better-optimized price for the users, but controlling various sources and high penetration of renewable energy, especially how surplus energy can be dispersed and share with all customers that could be the future direction of the research. However, artificial intelligence, sum of the products, Meta classification and regression fusion can help in this advancement. We considered half-hour energy consumption for monthly basis. If we can show real-time half-hourly price signals on the basis historical data considering with artificial intelligence that would be the real-time prediction. That could be future another direction of the research.

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