A Renewable Energy Grid Daily Pricing Model for Consumer

ASM Ashraf Mahmud
Computing Division
University of West of Scotland UK
ashraf.mahmud@uws.ac.uk

Paul Sant
Computer Science and Technology,
University of Law, UK
dr.paul.sant@gmail.com

***Abstract*—A Renewable Smart Energy Grid is a global challenge which has to address varied complex issues. In response to this challenge, we present an algorithm for Real-Time Price Suggestion (RTPS) that allows for utilisation within the Smart Grid (SG). Our model achieves a complex optimization of the personal (individual) energy needs of a consumer and minimization of their energy costs. As the SG represents a bi-directional grid the RTPS manages the balance between energy consumer need and a provider to optimize cost savings via a Demand Response (DR) model. The RTPS was designed and validated using real energy network data and has demonstrated that energy consumers can reduce their energy expenditure. Our model integrates the following metrics; Price Suggestion Unit (PSU), Price Control Unit (PCU), Smart Meter (SM) data and along with user appliances, the proposed Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm which varies prices on the basis of a users' consumption. Thus, we believe that the RTPS algorithm accommodates users' preferences and non-responsiveness in order to save their energy cost, thereby, safeguarding individual consumer rights and users' social welfare.**

Keywords—smart grid, demand response, stochastic approximation, energy demand, price suggestion

I. INTRODUCTION

Global climate change objectives are supporting a transition to net-zero across energy infrastructure and interdependent critical networks and services e.g. transport decarbonisation, carbon reutilisation for manufacturing etc.[1]. During the COVID19 pandemic, albeit energy demand has been reduced due to reductions in key areas such as commercial manufacturing and freight, the strategic investment into decarbonisation from the private sector and national governments remains unaffected [2]. Furthermore, the COVID19 pandemic resulted in significant curtailment of renewable generation within the UK, highlighting the importance of responsive flexibility and demand side response within the energy network [2]. The renewable energy transition is influencing all aspects of our energy infrastructure, not restricted to greener generation or storage technologies, but influencing how we plan, manage, regulate and trade energy. The non-Organisation for Economic Cooperation and Development (OCED) predicted that renewable energy demand is growing. Consumption would be increased by 70 % by 2050 [3]. Central to this revolution in our energy infrastructure is the omni presence of Big Data Analysis (BDA) [4]. BDA is central to the primary functions of our energy infrastructure and fundamental to the increasing use of Artificial Intelligence (AI)[5] in automated decision making for various operational and planning functions. The transition to net-zero has created challenges in how we ensure resilience e.g. continuity of energy supply, from intermittent renewable generation but also how we democratise energy to encourage positive consumer engagement [6]. Energy networks must operate within strict operational tolerances in order to protect the stability and quality of energy supply [7] Therefore, with consumers taking more control of their personal energy usage, and engaging in ancillary energy markets there is a potential for a decision making tension between the rights of the individual consumer and the needs of the community, regional or national energy system [8]. Furthermore, there can be some unintended consequences of decarbonisation, such as risks to social mobility within rural communities whose transportation costs can increase, thereby, prohibiting travel for employment or education [9]. Prior to COVID19 and in accordance with the Department of Energy & Climate Change Annual Report and Accounts [10] the evolving economies of developing nations had driven a growth in global energy demand. The current increasing world population [11] also led to an expansion of energy consumption. It can be assumed, that post COVID19 these trends will resume, and a key feature of this energy revolution must be to improve our understanding and optimisation of services with respect to how consumers engage with energy services and markets. Significant global investment is being made into modernising our existing energy infrastructure and establishing new green technologies for generation and storage[12]. The relationship between reliable energy access and quality of life metrics, including healthcare and education, is very well established. With a small increase in energy translating to a significant improvement in quality of life and social mobility.

Energy Demand Management (EDM) is strategic within the decarbonisation agenda of both residential and non-residential markets [2]. EDM looks to improve operational and planning strategies of meeting energy demand, wherein the objective is to minimise cost and reduce carbon. This field of research can involve data, physics based and fusion modelling [13]. DSR takes advantage of the fact that the Smart Grid (SG) provides a unidirectional platform for data and energy flows. With increasing use of Internet of Things (IoT) technology within the built environment e.g. homes, factories etc, it becomes possible to forecast energy demand with increasing ground up accuracy via aggregated data across multiple appliances and assets within buildings. DSR not only provides an opportunity for consumers to engage in energy and cost reduction strategies, but also to respond to the needs of the energy network. This can be extended to the emergent peer to peer energy trading market, either, individually or as community coalitions [14].

The Electricity Act 1989 privatised the British Electricity. It has a framework of privatisation of the electricity supply in the UK. It has done through Office of the Electricity Regulation (Offer) [15]. It helps develop competition between suppliers in the energy market. There are three performers' generators, suppliers and consumers who play the role to generate, supply and use the electricity.

Suppliers are using the embedded generators to avoid charges associated with transmission network. Avoidance of charge means embedded benefits. Ofgem has made various changes to reduce the benefits. [16].

With respect to engagement and responsiveness from these groups, it has been reported that there are typically two categories; (I) some are eager to reduce bills and engage, others are more passive to changing supplier or engaging with advice in behavioural changes; (II) some of them will have priority for comfort not for reducing the price [17]. Nonetheless, every customer should have the right to achieve an optimised price for their consumption. The research in this paper reviews, designs and validates a consumer centric solution for optimal energy pricing and usage, which also supports optimisation of the energy network. Our algorithm incorporates critical characteristics that defines the individual preferences for an objective in this paper reviews, designs and validates a consumer centric solution for optimal energy pricing and usage, which also supports optimisation of the energy network. Our research will strike a balance between them and propose a solution to it. [14]. This paper also discusses the current pricing methods, Demand and Response and the potential of other proposed systems [18] [19].

Section I of this research presents Introduction. With Section II, we described a review of Demand Side Response and Pricing Methods, Section III describes the Methodology, and Section IV describes the Proposed Model block diagram. Section V describes how proposed model works with the details of the algorithm designed. Section VI describes the experimental results. Finally, Section VII summaries the primary conclusions from this research.

II. DR (Demand Response) and Pricing Methods

The primary functions of DR (Demand Response) includes control mechanism, data analysis and decision-making. In the control based DR model, it is performed in a centralized manner, but it is difficult to implement in a large grid. In this type of DR, users can interact with each other to reduce their aggregate load. In a distributed manner, consumers can react to the system if it is critical. On the other hand, DR schemes are monitored and coordinated by a central controller using a centralised programme.

In DR management, varieties of pricing methods have been implemented [20] like Time-of-Use (TOU) and Inclined Block Rate (IBR) [15]. There are a number of peak pricing schemes, such as Peak Load Pricing (PLP), Critical Peak Pricing (CPP) and Variable Peak Pricing (VPP) that have been used in the existing UK market. In comparison, Real-Time based pricing schemes, such as Day-Ahead Real-Time Price (DA-RTP) and Real-Time Price (RTP), are explained within research [21]. In a time of energy system stress, customers receive different new prices which are unexpected, in order to mitigate risks within the energy network. Variable Peak Pricing (VPP), Peak Time Rebates (PTR) or Peak Load Pricing (PLP) are introduced where only peak price matters. It is measured based on average energy consumption. It is based on the feedback from the customers due to the high price and customer satisfaction was not guaranteed. Inclined block rate (IBR) [22] is used based on threshold load.

RTP pricing algorithm [23] proposed with Scheduling (ECS) device. The paper claims that aggregate load demand reduced energy consumption by using a stochastic approach [24] [25]. It estimates scheduling demand to minimize the electricity payment of the users without considering their responsiveness. However, there is no comparison between traditional price and experimental price in that research. They did not engage the users. It uses schedule-based appliances which are not fit for the current state of the SG. They did not consider the customers' preferences. To implement the model, every user must have scheduling smart devices to communicate their ECS, which is not possible for the current scenario in the world. We use the current state of real data in different buildings that are obtained from different appliances in our model. Our proposed novel Real Time Price Suggestions (RTPS) model answered all of the hypothetical questions. Our model RTPS compared the traditional price and model price [25] [19]. They used only customers' usages based on the fact that an optimised price may have been offered.

RTP programmes for various customers such as residential, commercial and industrial were effective. There is a logical relationship between the energy provider and users. An Energy provider can control a user's consumption remotely. They use the price-based programme to consumers who can shift their consumption during the day [26] because the Energy provider can use Direct Load Control (DLC) and a price-based load control programme. Nonetheless, RTP and Advanced Metering Infrastructure (AMI) [23] and the smart meter can be used for DR solutions.

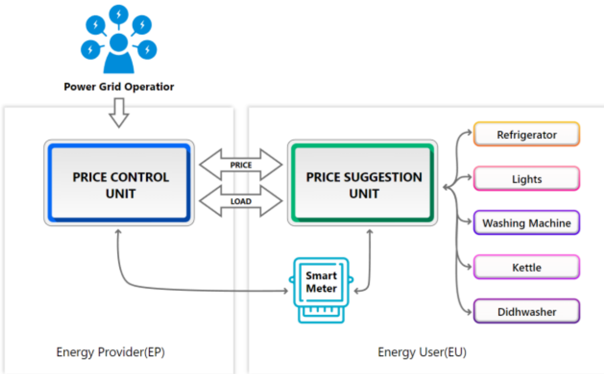

Fig. 1. Architecture of the proposed Model

Our proposed model is price-based DR which is working between energy supplier and energy users. Figure 1 shows how the architecture of the model works. Power Grid is connected to suppliers, users and their appliances. Fair charging is sometimes an issue in RTP to minimize the total cost or Peak-to-Average load [27] [25]. Our model addresses that issue, we have shown the fair charge is possible within the RTP framework. Coexistence and fair implementation [12] is challenging but it sometimes benefits the clients who will get a reduced price for their efforts.

The pricing model [28] with a Smart Meter (SM) and DR shows that some factors support the RTP like a SM, regulator interest in the DR programme and an organised electricity market. This Day-Ahead Real-Time Pricing (DA-RTP) model offers the optimal price assisted only by the retail provider by using Non-Linear Programming (NLP). It discusses RTP implementation which may be affected because of some technical issues such as the lack of smart metering, and communication and control systems. The paper [23] proposed a pricing algorithm with scheduling device ECS. We are not considering scheduling devices. We have discussed about this more at the end of the chapter of this paper. The research paper [29] discussed the DR model on the instability of power grids while RTP runs. The paper [30] illustrated load management strategy by using two case studies. It assumes that it allows energy usage control. It used heuristic optimisation techniques. The Quasi-Dynamic Pricing Model [31] was presented to minimise bills by using ToU. It assumes that energy cost depends on interruptible and non-interruptible jobs. It uses price and penalty term together.

Existing DR programmes generate inefficient price information [32] that can be solved by demand subscription. Considering subscribers [33] who share common energy sources, they would be equipped with an Energy Consumption Controller (ECC).

III. Methodology

Our model considers current electricity consumption in a time slot wise format with overall appliances. It also addresses user preferences with a stochastic approximation. Our research aims to develop a real-time optimised DR pricing model through a price suggestion unit to accommodate users' choice without interrupting their energy preferences. Our analysis is based on simulated energy demand data due to the constraints on real-world smart meter data. Our dataset is half-hourly basis 48-time slots and consequently, we analysed our model on a half-hourly basis. It could also be fine-tuned to consider smaller units of time if necessary.

The probabilistic nature of the data itself is a challenge for the SG [20]. Diverse customers' demand could have a potential impact on defining a unit price. In that regard, price segregation for different categorical customers could solve the problem. Our model can accommodate high or low customer demand; accordingly, it generates an optimised price. Usually, a heuristic approach picks up some combinations of input data, but not randomly and with no guarantee to find the correct optimal solution.

Considering all aspects, we have taken a stochastic-based approach by using Simultaneous Perturbation Stochastic Approximation (SPSA) [25] which can also handle non-a differentiable function and reach an optimal solution. There is a huge discussion on different optimisation techniques; comparing those techniques would be another dimension of the paper like reinventing the wheel in statistics. We have used techniques which are used to achieve our proven RTPS model.

We named our model the Real-Time Price Suggestion (RTPS) model. We have a Price Suggestion Unit (PSU) to address the energy bill and Peak-to-Average Ratio (PAR). Our model uses real data as mentioned earlier in different buildings that are obtained from different appliances in our model. So far, a variety of research has been undertaken related to Smart Grids, but these are lacking in addressing issues such as customer responsiveness and price optimisation for end users and energy providers.

IV. Proposed Pricing Model

The proposed RTPS model accommodates users' preferences by considering a user's price suggestion to save their energy cost. Implementation of this iterative algorithm of the Price Control Unit (PCU) means that it can minimise the PAR of the aggregate load based on information provided by the PSU. In the SG, RTPS model will work with an assumption that PSU (newly developed) would be keeping in the users' side and PCU in the Energy provider's side. An iterative stochastic optimisation technique SPSA [34]-[24] is used to approximate the gradient of the objective function which is minimised by changing the elements of the price parameter. The scenario would be modelled in real time to ensure the benefit of consumers and the energy providers are maximised [23]-[35].

The notations used for the algorithm

Symbols	Notation
l_{a_u}	Load per appliance and user
U	Total number of Energy consumers
a	One appliance
P	Price vector
t	Individual time slots
T	Total number of time slots
$\mathcal{T}$	All time slots for all users
r_{a_u}	Energy consumptions per slot

p_t	Energy Provider's price per unit
$l_{a_{u_t}}$	Load per appliance per user per time slot
L_u^t	Total power load
u	One User
min_t	Minimum price charged
max_t	Maximum price Charged
thr_t	Threshold Price based on threshold load
$\phi(P)$	Price objective function to be minimised
$\hat{g}^{\,i}$ (P^i)	Estimated gradient vector of ϕ(P)
$L_t\,(P)$	Total aggregate load at time t
σ^i	Step size in i iteration
K	The dimension of the vector
c	Coefficient
α	Positive constant
γ	Improvement coefficient
ε^i	Perturbation vector
I	The enhanced value of the iteration
A	Total number of appliances
$g_{max}(t)$	Maximum energy generation
g_t	EP's generation at time t
L_u	Total Schedulable load profile
P^i	Price parameter in i^{th} iteration
b	Defined building
rc	per half-hourly industrial running cost

V. How the propose Model works

A. Problem formulation in Price Control Unit (PCU)

Let us define a building user based total power load

$$L_u^t \triangleq \sum_{a\in A} l_{a_{u_t}} \tag{1}$$

Let us denote the minimum and maximum price parameters are min_t max_t and it can be expressed as

$$p_t\,(L_u^t) = \begin{cases} min_t, & if\ 0 \le L_u^t \le thr_t \\ max_t, & if\ L_u^t > thr_t \end{cases} \tag{2}$$

where thr_t is the threshold price parameter that can be selected by the energy provider that is based on the offices' usual energy consumption, for example, the building energy consumes 40 kWh in a particular half-hour time slot and p_t the actual price determined by an energy provider at time t and the total day has been divided into 48 time slots, on a half-hourly basis that is defined as T, where $t \in T$. To reduce the PAR of aggregate load, define $P_t \triangleq (min_t\ max_t\ thr_t)$ as a vector of the total set of price vector P = ($\mathrm{P}_1, \ldots \ldots \ldots . . \mathrm{P}_T$). The price of the electricity depends on total half-hourly basis energy consumption.

Considering the RTP half-hourly basis optimised price value for the clients, we define

$$\underset{\mathrm{P}}{minimise}\ \phi(P) \text{ with a constraint to}$$

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

where

$$\phi(P) = \max\,\{L_1\,(P)\,\ldots . L_T\,(P)\} \tag{3}$$

The price objective function $\phi\,(P)$ is stated with minimum and maximum price functions [25] [25].

$$\mathrm{P}^{i+1} = \mathrm{P}^i - \sigma^i\,\hat{g}^{\,i}\,(\mathrm{P}^i) + \epsilon^i \tag{4}$$

where $\hat{g}^{\,i}$ (P^i) is an estimated gradient vector of ϕ(P), in the i times iterative process, P^i would be input vector and its step size would be $\sigma^i > 0$ that can be reduced when the number of iterations increases to make it convergent. The coefficient magnitude of perturbation is $c^i > 0$. Calculate σ^i and c^i as per the proposition of J, spall [24]

$$\sigma^i = \frac{\sigma}{i+1+\mathrm{I}^{\alpha}}\,,\ c^i = \frac{c}{(i+1)^{\gamma}} \tag{5}$$

It is essential to take all positive values of $\alpha, \sigma, \gamma\ and\ c$. To enhance the convergence we take $I \ge 0$. Calculate $\hat{g}^{\,i}$ (P^i) by using the equation below

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

$$= \frac{\phi\,(\mathrm{P}^i + c^i\varepsilon^i) - \phi\,(\mathrm{P}^i - c^i\varepsilon^i)}{2c^i}\,\left(\frac{1}{\varepsilon_1^i}, \ldots \ldots\ \varepsilon_{\mathrm{K}}^i\right) \tag{6}$$

where $\varepsilon^i \triangleq (\varepsilon_1^i, \ldots \ldots . \varepsilon_{\mathrm{K}}^i)$ is a bias term with $\varepsilon_j^i \in \{-1, 1\}$.

B. Problem Formulation in the Price Suggestions Unit (PSU)

The RTPS generates a daily basis price suggestion which is modified from the model [36] in figure 3. PSU is connected to the SM and the algorithm of the daily Real-Time Price Suggestions defined below. Let us denote the buildings as b_1, $b_2 \ldots b_n$, and time slots are defined as $t_1, t_2 \ldots t_p$. We can have the matrix as

$$\begin{pmatrix} b_1 t_1 & \cdots & b_1 t_p \\ \vdots & \ddots & \vdots \\ b_n t_1 & \cdots & b_n t_p \end{pmatrix} \tag{7}$$

Make a summary matrix for each building with all time

Slots

$$\begin{pmatrix} \sum_{i=1}^{48} b_1 t_i \\ \vdots \\ \sum_{i=1}^{48} b_n t_i \end{pmatrix} \tag{8}$$

Another summary matrix for each time slot with all buildings

$$\left[\quad \sum_{j=1}^{n} b_j t_1 \ \ldots\ \sum_{j=1}^{n} b_j t_{48} \right] \tag{9}$$

Make an average matrix for each building with all time slots. There are conditions would be applied. It would be compared with the whole load and find the lowest possible value.

$$\begin{pmatrix} \dfrac{\sum_{i=1}^{48} b_1 t_i}{48} = a_1 \\ \vdots \\ \dfrac{\sum_{i=1}^{48} b_n t_i}{48} = a_n \end{pmatrix} \tag{10}$$

And another average matrix for each time slot with all buildings

$$\left[\frac{\sum_{j=1}^{n} b_j t_1}{n} \ldots\ldots\ldots\ldots \frac{\sum_{j=1}^{n} b_j t_{48}}{n}\right] \tag{11}$$

$$\text{Overall average} = \frac{\sum_{j=1}^{n}\sum_{i=1}^{48} b_j t_i}{n} \tag{12}$$

Make a surplus matrix for each building with all time slots

$$\begin{pmatrix} b_1 \sum_{i=1}^{48} t_i - \sum_{i=1}^{48} a_{1i} \\ \vdots \\ b_n \sum_{i=1}^{48} t_i - \sum_{i=1}^{48} a_{14i} \end{pmatrix} \tag{13}$$

As to make changed position matrix from equation 9,

It makes a surplus matrix if

$$\begin{pmatrix} (b_1 t_1)_c ? & \cdots & b_1 t_{48})_c ? \\ \vdots & \ddots & \vdots \\ (b_n t_1)_c ? & \cdots & b_n t_{48})_c \end{pmatrix} \tag{14}$$

where $(b_1 t_1)_c = b_1 t_1 - a_1 \cdots (b_1 t_{48})_c = b_1 t_{48} - a_1$

subject to $b_1 t_i > a_1$, where $i = 1,2 \ldots..48$

where $(b_1 t_1)_c = (b_1 t_1) - a_1 \cdots (b_1 t_1)_c = (b_1 t_{48}) - a_1$

$\vdots$

$(b_n t_1)_c = (b_n t_1) - a_n \cdots (b_n t_{48})_c = b_n t_{48} - a_n$

subject to $b_n t_i > a_n$, where $i = 1,2 \ldots 48$

The algorithm starts from the lowest changed element of the lowest total load per time slot. It checks with the particular building average. Then it fills the load in the lowest position and makes a surplus load matrix if it exceeds the average load of the particular time slot. Again, check another lowest load position. If necessary, it takes the load from the relevant surplus position. Then, it fills the load to the particular position and makes it into the average level, subject to the total amount of a load of that particular time slot that would not exceed the overall average load. Re-organise the latest changed matrix; process two repeats until the element of surplus matrix < 1, which we call an insignificant adjustment amount. We find the sum of per building time slots or total energy consumption per day:

$$= \sum_{t=1}^{p} b_n\, t_p \tag{15}$$

Sum of total building consumption per time slot

$$= \sum_{b=1}^{n} b_n\, t_p \tag{16}$$

Find per building per slot average

$$= \frac{\sum_{t=1}^{p} b_n t_p}{p} \tag{17}$$

Total building per slot average

$$= \frac{\sum_{b=1}^{p} b_n t_p}{n} \tag{18}$$

Find peak load from every time slot in each building in the time slot $b_1 t_4$. Find peak load from all buildings overall, for example in time slot t_4, peak of t_1, $t_2 \ldots t_p$.

C. The Process Involved with the Price Suggestions

Minimising the cost function, the model provides the optimal price in the PSU for the customers and expect from the user's responses, however, if users are non-responsive it goes to actually charge for the users in the PCU. Again explain from the model [36], PCU is connected with PSU.

PCU is at the side of energy provider which is connected to the main power plant. The flowchart of the proposed structural model is shown in figure 2. Price suggestions made based upon the selected price value of the energy provider. The user will be notified via a user interface by using a browser on their PC or in the PSU itself. The message should be advised for users. For example, there would be instructions to the user that they should shift their flexible appliances' load. The energy provider executes the unit price, RTPS generate the actual price at a real-time basis which is optimised price calculated by the SPSA algorithm based on usage. From the energy provider, the slot can be suggested for the users to shift their load based on historical data like slot 3-5, 6-9, 3-12 etc.

D. Price Suggestion Unit (PSU) interface for users

The user interface would help the user to decide which time slot would be useful for them to shift their load based on suggestions. A user can choose non-flexible appliances to deviate from suggestions. If a user exceeds the limit of the budget, it will show as red, and it would indicate that the user is outside the optimal estimate.

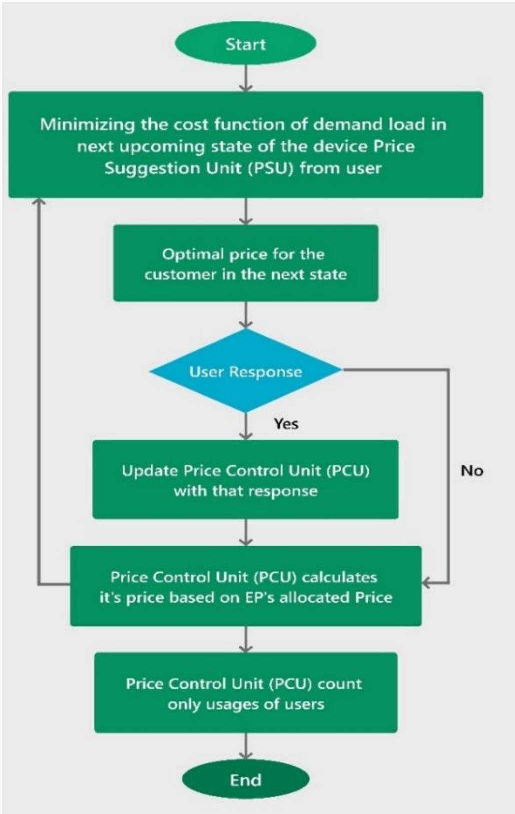

Fig. 2. Proposed model's flow chart

VI. EXPERIMENTAL RESULT

In this section, we illustrate the performance of the system which is equipped with an algorithm for a PSU and PCU. With the algorithm implemented in the system, we delineate the overall experimental result and test the system. Using the SPSA optimisation technique, the system generates total prices using a flat-rate price and it also generates a real-time price. The system uses minimum, maximum prices on a real-time basis.

We decompose the whole analysis into four different categories. Firstly, we analysed how the buildings as a whole is consuming energy and how an individual building is using its energy. Secondly, we consider how the overall flat-rate price is implemented in the grid and also as part of an individual building's flat-rate price daily basis analysis. We implemented an RTP analysis on the daily basis. By considering our model, we analysed the case without considering the user's response price calculation and also analysed the other case by taking users' responses into consideration. Thirdly, we endeavour to show how users made cost savings with the consideration of flat-rate and Real-Time Pricing. We have also shown how RT price selection can be applied to every building. Fourthly, we have shown how the Peak-to-Average Ratio (PAR) is reduced on the Energy provider side where they can reduce their cost by reducing their overall peak load, which is very significant for them as the energy provider's cost depends on overall peak demand from energy users. We have shown the daily price suggestions where the user needs to shift their load to save their money.

We have analysed data from the two different institutes. Fig. 3 shows the all 14 buildings load distribution. For example, we have found from Department for Education (DfE), the small buildings consumed, on average, 1291 kWh, the biggest building consumed 20,480 kWh, and their average (across all four buildings) consumption is 8147 kWh. The other two buildings consumed 3906 kWh and 6916 kWh. So, the average demand is 8147 kWh. The buildings are not similar: they are very diverse, some of them small, medium or large. It shows that our model accommodated the high variability of data.

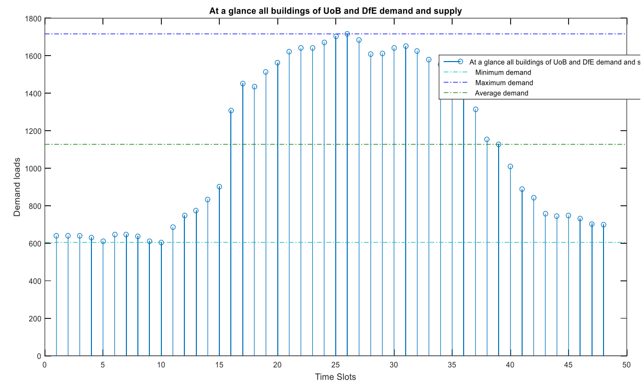

Fig. 3. Energy provider's supply regarding all users' demand from all buildings

The flat-rate pricing in figure 4 does not treat the energy users fairly because the standing charge for every type of the customers is the same. Sometimes, the energy provider cannot collect the energy consumption from the energy users regularly as energy users do not want to provide their meter readings on a regular basis because it is time consuming for them. Therefore, the energy provider produces an estimated bill for energy users as the whole system is a uni-directional communication.

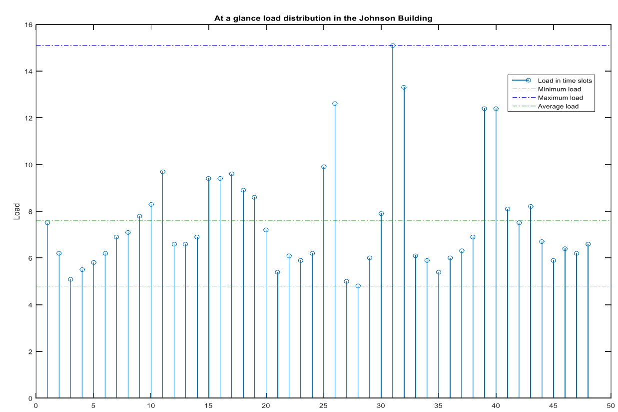

Fig. 4. Load distribution in the Johnson Building (Sample)

They are being charged on a flat-rate basis. If the energy provider fails to collect a meter reading from the users on a monthly basis, then they have to adjust the load in the month of receiving the actual meter reading. Ironically, the cost of the users may be high or low to adjust the bill. The energy provider charges the energy users if energy users have high usages.

A. *Real-Time (RT) Price Selection in different Buildings*

The energy provider decides unit price by considering the marginal cost of their energy buying price from the power transmission.

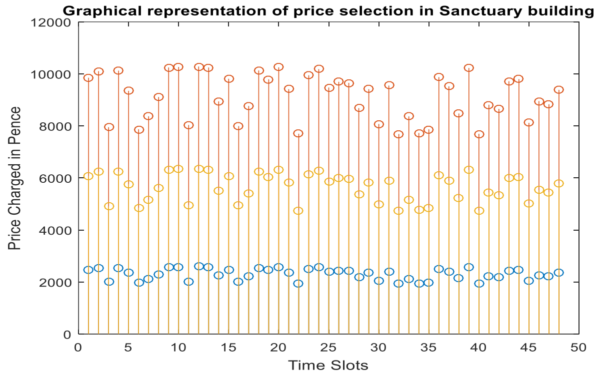

Fig. 5. Max or Min charges in different time slots for a building Sanctuary

Then this unit price would be calculated with the price vector where users receive optimal price. We have used the same unit price for ToU flat rate and real-time pricing for our experiment. The RTPS uses a dynamic charge, either pricing maximum or minimum on the user profile on a half-hourly basis. The figure 5 shows real-time max or min charges in different time slots per day. We have explained this in equation 2. User responses calculated in PSU.

B. *Real-Time Price Calculation*

The Johnson building (sample) RT price distribution is shown in Fig. 6. The RT price is charged by load consumption on a real-time basis. Some of the time slots are highly charged and some of them are low.

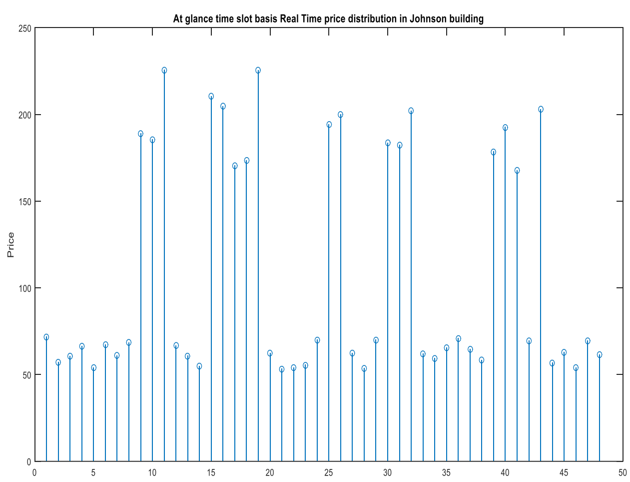

Fig. 6. Time slot basis real-time price distribution in the Johnson building

For example, time slot numbers 11, 19, 32 means 5 am, 9 am, 3.30 pm, because they exceeded the threshold load and the RT price was high. Fig. 7 shows the price difference in the sample building in different time slots.

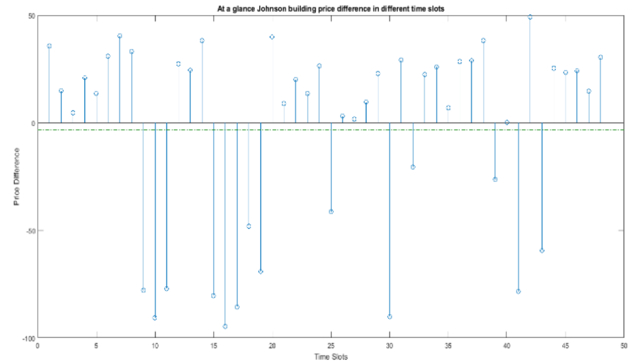

Fig. 7. Johnson building price difference in different time slots

C. *Daily basis Load Shifting Suggestions in different buildings*

In accordance with the previous day total energy load consumption, the price suggestion unit would make a half-hourly suggestion for the next day. This would include how much load they can shift from the one-time slot to another based on their threshold load consumption. The algorithm is able to calculate, on a real-time basis, for each of the buildings and make a suggestion for each. This graphical representation in Fig. 8 shows the amount of reduced load (represented by downward bars) and the amount of increased load (represented by the upward bars).

Energy consumers can, therefore, understand how much energy should be reduced in particular time slots in order to deliver cost savings. The algorithm generates suggestions for each building.

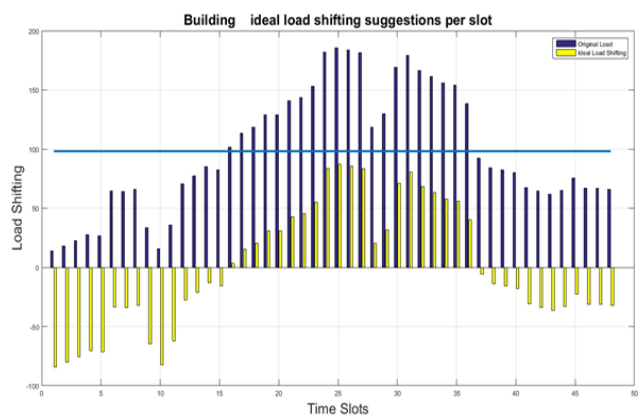

Fig. 8. Real-time ideal load shift suggestion per time slot for a building

A load shifting suggestion signal is generated for each user through the price suggestions unit. In that building, figure 8 shows that its energy consumption is significantly above the average from 12:00 pm to 1:00 pm, and 3:00 pm to 3:30 pm. The PSU would suggest those loads shift anywhere that is below the average, not in the morning or afternoon, rather in different time slots in the whole day in a similar fashion. We measure the response from the users. It would be very difficult to ensure the data collection regarding the response from the users. We made a prototype as our price suggestion unit is totally new and a novel contribution to the system. It is not possible at this stage to build a commercially viable unit. We have tested this model in simulation. We counted user responses randomly and constituted the results. Daily RT price savings for all DfE and UoB buildings considering users' response.

We have calculated the daily base per building real-time price savings after load shifting in the DfE and UoB buildings. The figure 9 shows that all 14, four buildings of DfE and ten buildings of the UoB reduce their bill after real-time pricing is implemented. We can see all the building individually saved the bill.

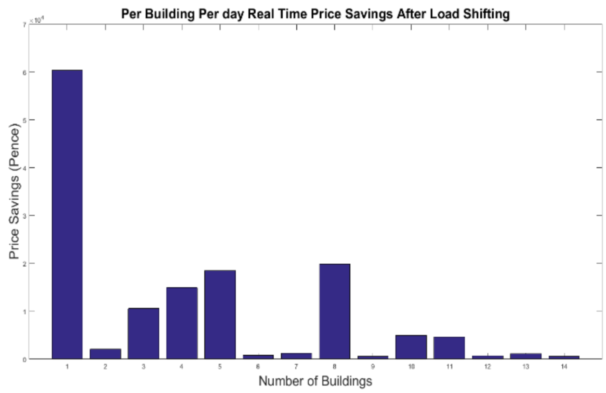

Fig. 9. Per building per day real-time price savings after load shifting

D. Daily basis PAR reduction

Considering the daily basis of all building loads, we calculated PAR after receiving the response from users. It shows that the system manages to reduce the PAR, which is 1.5 to 1.3. The figure 10 shows the overall reduced PAR in the SG.

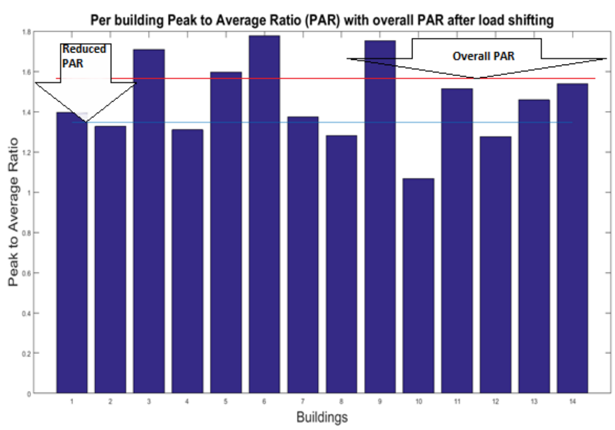

Fig. 10. Per building PAR with overall PAR after load shifting

VII. Conclusion

In this research we have identified the trends in BDA and AI and the associated conflict between DSO and individual consumers. To support an optimal and tailored real-time pricing model, our approach is based on a domestic smart meter acting as a centralised hub for consumer appliances. Our model then integrates a Real-Time Price Suggestion (RTPS) model with a Price Suggestion Unit (PSU) connected to the SM. The network operator side of the SM has a Price Control Unit (PCU) a real-time DR in the SG.

Particularly, the result shows how the system benefits all buildings and energy providers. We checked the results based on a daily basis data. Energy consumers saved significant costs and the overall PAR was also reduced, which is of benefit to energy providers.

A stochastic approximation method SPSA is used to generate prices and provide suggestions for users for when they should shift their load. The Energy provider can reduce the PAR, and we provide a detailed discussion in the experiment and result chapter that explains how the costs are saved.

The RTPS DR model architecture where PSU would connect with a SM to receive energy consumption signals. PSU is connected to PCU. The energy provider would allocate the price value in the price parameter of the PCU, then it calculates the optimised price through the pricing algorithm along with the price suggestion algorithm provided in the PSU. It generates an optimised price signal to the users by considering users' threshold consumptions. The RTPS model calculates the optimised price in each of the time slots. There are price signals in each time slot, maximum or minimum. The energy users would be charged based on their threshold energy consumption. If the user goes beyond the threshold they would be charged maximum price otherwise minimum on a real-time basis. The model generated the suggestions based on users' energy threshold consumption. The user responds to the suggestions to reduce their bill. However, if they are non-responsive still they would achieve significant price savings in terms of the traditional ToU price which is in the existing market.

This RTP based DR model is being developed and it works with the renewable and non-renewable energy. Results show that RTP is better than ToU pricing methods on daily basis algorithms in the PSU and PCU by using SPSA. Price suggestions guide the users' time slots in order to manage their load more effectively and reduce the overall PAR through the use of a PSU that is a fundamental contribution of this research.

Finally, the model has been validated by building a hardware prototype. This model significantly reduced the Energy users' bill, and Energy Provider's cost as the PAR is reduced significantly using this approach. This model benefits both energy consumers and providers. It benefits all level of customers as data has been tested with PCA as real data's standard deviation is high. It also accommodates the probabilistic nature of data. It maximises social welfare.

Moreover, it accommodates the energy provider's interest. Energy providers are being charged by power generation 'peakers' basis. Where, the 'peakers' mean the high demand period of electricity over the day. Consequently, the energy provider is keen on minimising the Peak-to-Average Ratio (PAR) to reduce their cost.

RTPS model reduces the Peak-to-Average Ratio (PAR) and provides an optimised price on a real-time basis to customers. The future work is envisaged to revolve around the use of multiple energy providers and sources where surplus energy can be shared within energy users. However, the model can be fine-tuned with a hybrid DR approach which is priced and incentive together.

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