Personalized Pricing: A New Approach for Dynamic Pricing in the Smart Grid

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***Abstract*—Among many key subjects in the smart grid technology, Demand Side Management (DSM) which is one of the common and popular subjects interests researchers on controlling and monitoring customers' consumption activities. In reality, DSM involves any activities that impress customer's consumption levels in a power grid system. This usually happens by means of employing new policies by utility companies, defining suitable pricing schemes that guarantee grid's continual working and using effective scheduling approaches to adjust hourly customer's consumption levels, especially on peak-time hours. Among them, pricing methods are very important and effective in controlling customer's consumption patterns. Real-Time Pricing (RTP) and Time of Use (TOU) pricing are common approaches which are being employed by many utility companies and are mostly dependent on the grid's dynamic load behavior. In addition, real-time pricing methods adjust real-time prices based on grid's real-time demand level dynamically. In this paper, we propose a new pricing method that not only makes use of grid's real-time consumption data but also considers consumption levels of each customer and define real-time prices individually (Personalized Pricing). This means that the consumption price for each individual customer will be adjusted by the changes that occur during the course of power consumption and also reflect each individual customer's habit of using electricity. In this way, our proposed method can consider both grid and individual customer's consumption level to adjust real-time prices. Generally personalized pricing is a type of an incentive-based DSM model that can impress customer's consumption levels by persuading them to decrease their consumption levels during peak-time hours and updating each customer's consumption prices individually. However, individual satisfaction is a more important capability that lies at the heart of Personalized Pricing. Our results also intensify that most of our customers in the grid will decrease their consumption levels during peak-time hours to reduce their electricity consumption costs.**

Keywords-demand side management; dynamic pricing; smart grid

I. INTRODUCTION

The ever increasing number of electrical devices and rapid movement of technology would emerge new demands to consume more electricity for individual persons to satisfy their needs. In addition, cities and urban facilities are vastly growing which introduce an even more need to electricity power and to develop more potential power grid infrastructures to meet the new flooding of demands. Therefore, making use of modern demand management methods in electrical grids is necessary.

Based on what has been mentioned before, different methods are being used in forms of DSM approaches to monitor and control demand levels in a power grid to provide efficiency in the grid. DSM is also low cost and can play a pivotal role in resource adjustment and availability [1]. There are also fruitful researches which have been carried out in the area of demand side management that we are going to make a review on the most highlighted ones. In [2] there is a discussion about a new scenario in which they are trying to convince selfish customers to reduce their consumption levels. The paper speaks about a new method to persuade customers to shift their consumption from peak-time to off-peak hours. The authors in [3], introduce a time-based method which is based on daily real-time pricing. The paper focuses on an hourly optimized power consumption by the use of customer's smart meters. There are another papers which proposed a new controlling system that make use of power storage facilities and electricity power generators in a smart home that is accompanied by a scheduling program to optimally use electricity resources [4]–[6]. Similarly in [7] and [8] a new mechanism is offered for scheduling customer's consumption pattern to reduce consumption levels at peak hours. The mechanism is called load-shifting that enables optimized use of energy by the use of shiftable devices. On other methods of real-time pricing, prices vary when total grid consumption levels will change and it can be also adjusted with regards to time. It has been proved that pricing strategy has a direct effect on the amount of power consumption. So, dynamic pricing has been introduced as a method for decreasing and shifting the customer's power demand. So far, many studies have been done that represent a variety of pricing methods which have their own benefits. Flat pricing was the first method of pricing in the traditional electricity grids which makes use of a definite price for all the customers in the grid in all the hours during a day. In this way, the only approach to reduce the consumption levels is to ask customers to reduce their consumptions levels, usually in case of emergencies [3]. Another method is Time-of-Use (TOU) pricing, that is famous in North America, European Union and even developing countries. The method divides a day in to three periods, on-peak, mid-peak and off-peak hours and then define suitable prices for each periods correspondingly [9]. Results also confirm that the method will reduce the electricity consumption levels more efficiently than methods such as flat pricing. Critical Peak Pricing (CPP) is another pricing method in which there is a pre-defined price that will be set in case of critical demand situation to impress customer's consumption levels [3]. Very similarly, Peak-Load Pricing (PLP) also uses a pre-defined price to use in peak-time hours to persuade customers to reduce their consumption levels [10]. In [11], they define an Inclining Block Rate (IBR) pricing scheme to control the dynamics of grid's consumption levels. In [12] and [13], authors also propose a method that consider a combinatory of load and price dynamics that can affect each other in a proper manner. In this method as the load goes up the price will raise and price goes up customers try to consume less than before. In this way, to minimize electricity consumption costs, customers should modify their habits of power consumption to meet the price of the grid at each time during their power usage.

After reviewing the literature, it can be completely understood that most of the previous work adjust grid consumption costs by detecting customers' consumption levels. However, in our proposed model we define a new approach that makes use of both grid consumption levels and individual customers' levels of demand to set appropriate pricing levels for each customer separately. Also in our study, we consider the power supply as a resource. This resource is fairly shared between all customers in the system. For this purpose, at first we allocate each customers definite amount of electricity at each time slots and then decide to calculate the cost of consumption. As long as the customers consume power less than their shared, the customers are charged by a low price. This kind of customers are named "good-behavior" customers. Those customers that consume energy more than their allocated shared, are charged by high price and named "bad-behavior" customers.

The rest of the paper is organized as follow: In the next section we will introduce the proposed system model and explain our method in details. In section 3, we will present the simulation results and compare them with the TOU method. Finally, section 4 concludes the paper.

II. System Model

In this section, we introduce our new proposed pricing approach which we called it: "Personalized Pricing". We define a function that limits each customer's consumption level to a specific amount of allowable electricity usage by determining each customer's features. In most of the real-time pricing methods, adjusting customer's consumption prices per each Kilo-Watt of electricity power is done by considering the total demand levels of the grid. However, in the "Personalized Pricing" method as aforementioned, the customer's consumption prices will be adjusted by considering each customer's consumption levels individually. This will be done through an incentive-based function that persuades grid's customers to reduce their consumption levels.

Indeed, in our proposed model, we define a quadratic function by considering the profits of utility companies and customers. Although, in [14] which the pricing indicator is depends on total electricity power consumption of network, in the "Personalized Pricing" indicators are defined individually and based on each customer's demand and allocated powers. These causes change customer's price when their individual consumption goes up in comparison with their allowable power. In addition, in our proposed model, there is an infrastructure of data collections that consists of smart meters that are placed at customer side. Online customer's consumption information is collected by utility companies at specific time intervals. Each customer has been already informed about his/her allowable electricity power. Fig.1, represents a flowchart of our proposed model. This flowchart should be applied to each customer. As shown in this figure, at first we need household information to allocate power coefficient to each customer. This information is utilized to calculate the customer's share of supplied energy. After that, at each time slot, the customer's consumption is compared with his/her allocated power to calculate the electricity price.

A. Power Allocation

Consider a region with N different customers. The key idea behind our proposed pricing method is to control customers' consumption levels by defining a specific function to limit customers' allowable usage levels in response to their real-time consumption levels. Similar in basis but different in method, in some of the selected studies in pricing methods, the authors considered household features to recognized the consumption levels of their customers [15]–[18]. However, in our proposed method we also consider some important features of customers to determine the amount of power that is necessary to be allocated to them for their future consumptions. Most of studies determining household features for understanding amount of power consumption by each household, without paying attention to amount of electricity will be suitable to allocate them. We choose six important household features which directly affects on customers' consumption levels. Suppose α_i represents the normalized allocated power of each customer $i \in N$ in the region. This parameter is defined as a linear sum of each pre-defined parameter $a_{j,i}$ which i represents the customer number and j corresponds to each customer's household features. Variable $a_{j,i}$ represents different household features which are obtained as follows: $a_{h,i}$, $a_{s,i}$, $a_{r,i}$, $a_{o,i}$, $a_{a,i}$ and $a_{d,i}$ that are stand for home type (apartment or house), home size (square meters), number of rooms, age of home and average power of household appliances of customer i, respectively. The normalized allocated power $\alpha_i, i \in N$ is defined as below:

$$\alpha_i = \sum_{j=1}^{F} w_j . a_{j,i} \tag{1}$$

Variable F is the number of features (here $F = 6$) and $w_j \in [0,1]$ is the normalized weight factor which represents the importance of the feature j in the power allocation. Note that the values of w_j are chosen so that $\sum_{i=1}^{N} \alpha_i = 1$, which means that the total power allocated to the customers should be equal to the total power supplied in the grid. We suppose that the amount of α_i remains fixed for each customer in the region. If there is any significant changes in one or some customers' features, the utility company should recalculateα_i. Suppose $G_{s,h}$ denotes the power supplied by the utility company at time hour h. As mentioned before, $\alpha_i$represents a normalized coefficient for allocating customer's share of power. Let $p_{i,h}$shows the allocated power to customer $i \in N$ at time slot h. $p_{i,h}$is calculated as follows:

$$p_{i,h} = \alpha_i \times G_{s,h} \quad , \quad \sum_{i=1}^{N} p_{i,h} = G_{s,h} \qquad (2)$$

At the beginning of each period (e.g. an hour), the amount of $p_{i,h}$ will be calculated due to the fact that $G_{s,h}$ is dynamic and will be changed instantaneously. We define vector G_s as the daily power supply as $G_s = \{G_{s,1}, G_{s,2}, \dots, G_{s,24}\}$. It is important to mention that in our proposed model, the utility company generates electricity in response to hourly power demand levels in the grid.

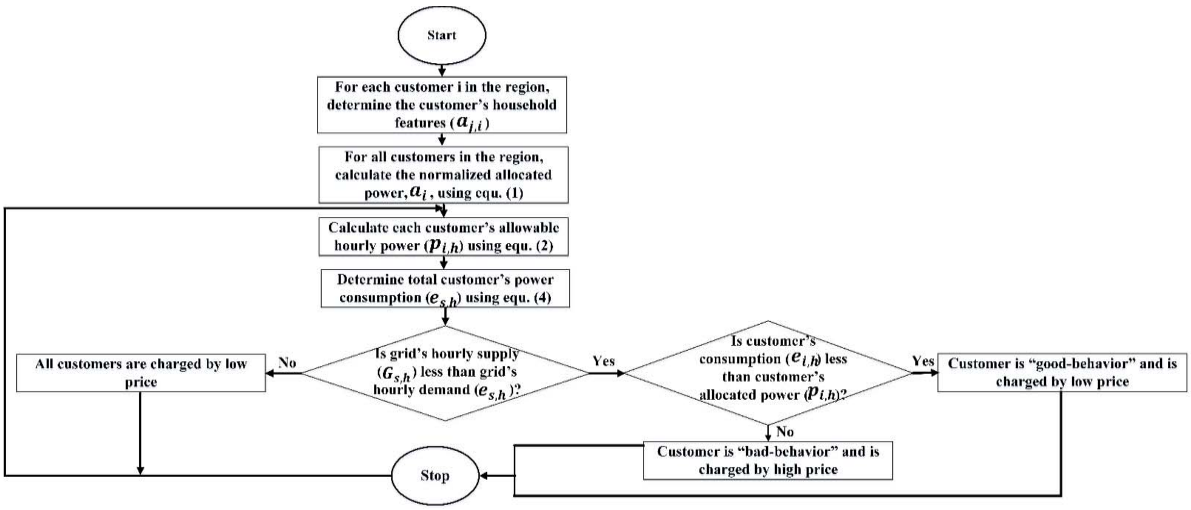

Figure 1. Flowchart and logical model of the proposed model.

B. *Personalized Pricing*

The "Personalized Pricing", is the core of our model in which each customer in the grid pays based on his/her consumption level at each hour h. We consider N customers in the grid who consume electricity power and their hourly consumption levels are reported to the power utility company to calculate their cost. In the "Personalized Pricing", the cost of each customer's consumption levels is calculated individually as indicated before. Suppose$e_{i,h}$represent the hourly power consumption for the customer i in the system. Therefore we have $e_i = \{e_{i,1}, e_{1,2}, \dots, e_{i,24}\}$which indicates the consumption levels of customer i during a day. In addition, $e_s = \{e_{s,1}, e_{s,2}, \dots, e_{s,24}\}$ shows the total electricity consumption level at each hour in the region. $e_{s,h}$is calculated as below:

$$e_{s,h} = \sum_{i=1}^{N} e_{i,h} \qquad (3)$$

Note that in normal condition to avoid blackouts the following inequality should always be satisfied:

$$G_{s,h} > e_{s,h} \qquad (4)$$

However, in case of power shortage in the grid, there should be considered some more expensive power generation facilities to satisfy this huge power demand levels in the grid. The "Personalized Pricing" is based on the amount of electricity that is allocated hourly to each customer individually and the amount of power that each customer consumes in each hour during a day. We also classify grid's customers in two groups: "good-behavior" customers and "bad-behavior" customers. The "good-behavior" customers are those customers who consume electricity power less than their allocated consumption limit while "bad-behavior" customers are those who consume more than their allocation power limit. The proposed pricing function is defined as below:

$$\cos t(e_{i,h}) = \begin{cases} e_{i,h}.c_{1,h} & if\ e_{s,h} \le G_{s,h} \\ e_{i,h}.c_{1,h} & if\ e_{s,h} > G_{s,h}\ and\ e_{i,h} \le p_{i,h} \\ p_{i,h}.c_{1,h} + c_{2,h}.(e_{i,h} - p_{i,h})^2 & if\ e_{s,h} > G_{s,h}\ and\ e_{i,h} > p_{i,h} \end{cases} \qquad (5)$$

In this function if total consumption level (demand) in the grid is less than the total power generated (supply) in the grid, then all customers are charged with a low price rate $c_{1,h}$ that shows the power consumption price at hour h. This price is the lowest price that will be applied to all the customers. The second term in the cost function shows that for the "good-behavior" customers who consume energy less than their share, the price is always low regardless the peak condition in the grid. In the other words, the customer's consumption costs will not be changed if the consumption level is less than the power allocated limits as defined by appropriate customers and to persuade them with satisfying incentives, their consumption costs will not be increased. The "bad-behavior" customers who consumes more than their allocated power, the cost will increased by a quadratic function with parameter$c_{2,h}$which is always greater than$c_{1,h}$. We should mention that in our model $c_{1,h}$ is always fixed whereas $c_{2,h}$ is dynamic and will be changed based on the total power generation costs by the utility company at the moment. Peak-time in our model is defined when the total power consumption level of the grid ($e_{s,h}$) is more than of the total power supplied ($G_{s,h}$).

III. SIMULATION RESULTS

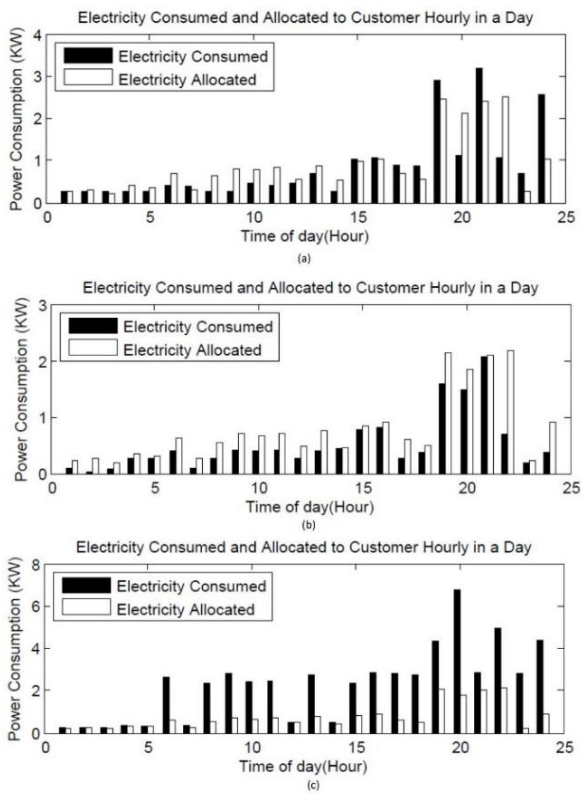

Figure 2. Customer's electricity consumption in a day a) “usual” customer b) “good-behavior” customer and c) “bad-behavior” customer.

In this section, by using software simulation we evaluate the effectiveness of the proposed “Personalized Pricing”. We in addition, compare our proposed model with the standard TOU pricing model which is used in many utility companies such as Ontario Energy Board [19]. In our stimulation scenario, we consider 10 customers for which we consider a random number of appliances. We choose 10 different appliances that are mostly used in customers' homes. Amount of power appliances need (KWh) and also usual duration of each appliance are the inputs which are needed in our simulation. We also consider utility companies that are equipped with some power generators to produce the essential electricity power for the whole grid. It is usual that in peak hour the generators do not produce enough electricity to meet the demand levels in the grid. Therefore to address this problem, the utility companies buy electricity from stand-by market which is usually more expensive than normal condition. Furthermore, using theses stand-by generators is not enough clean for the environmental. For sure if such an event happens (peak-hours), the utility company should pay more for the operational costs of the generators that will eventually increase the power consumption costs in the grid which will be introduced by parameter $c_{2,h}$ as mentioned before. In addition to “good-behavior”/“bad-behavior” customers which always consume less/more power than their share, we define the “usual” customers who sometimes consume more and sometime less than their share. In the simulation scenario, customer #1 and #10 are always “good-behavior” and “bad-behavior” customer, respectively. The other customers are supposed to be “usual” customers. For instance, we choose customer #3 and #7 to show their appliances features and α_i which are calculated with (1). Customer #3 whose house with total floor of area 227 square meters, 5 rooms, 4 occupants, age of house is about 7 years and 159.083KWh for average power of household devices, has the value of α_i equal to 0.1098. For customer #7, whose apartment with total floor of area 74 square meters, 2 rooms, 4 occupants, age of apartment is about 6 years and 225.528 KWh for average power of household devices, has the value of α_i equal to 0.0892.

Fig. 2, for three types of customers including: “usual”, “good-behavior” and “bad-behavior”, shows a particular customer's consumption in a day. The white bar shows the hourly allocation power and the black bar shows the hourly power consumption. We can see that in some hours “usual” customers consume more than their allocated power. In this figure, a useful comparison between the amount of power consumption level and the amount of power being allocated is shown. Fig. 3 for those customers whose consumptions have been already depicted in Fig.2, shows a comparison between TOU pricing and “Personolized Pricing” methods in terms of power consumption cost. It can be also understood that the proposed pricing provides low cost for “good-behavior” customers comparing to the TOU method. Furthermore, “bad-behavior” customers charge with high cost especially at the peak hours. Fig. 4 shows a comparison between the amount of power being generated in the grid versus the amount of power being consumed. Note that, when the demand is more than supply, the utility company shoud buy energy from the stand-by market which is usully more expensive. Fig.5 shows the total cost of electricity consumption at the end of each day with two different methods of pricing, “PersonalizedPricing” and TOU. The horizental legend in this figure shows the customer number in the grid. As it is shown, for the first customer who is always “good-behavior” the total cost with “Personolized Pricing” is less than that of TOU pricing, while for the last customer who is always “bad-behavior” customer, the cost is much more than TOU method. For the other users (“usual” customers) who have good or bad behavior in different hours of a day, the total cost may be more or less than that of TOU method, depends on their consumption level. As we can understand from the simulation results, we could recognize that our proposed model results in lower costs for the good behavior customers who always consume lower electricity power than their allocated power. This method seems to cause more temptations in customers to reduce their consumption levels. Also when grid goes in to peak hour, only customer's cost whose consumption is more than their allocated power will increase.

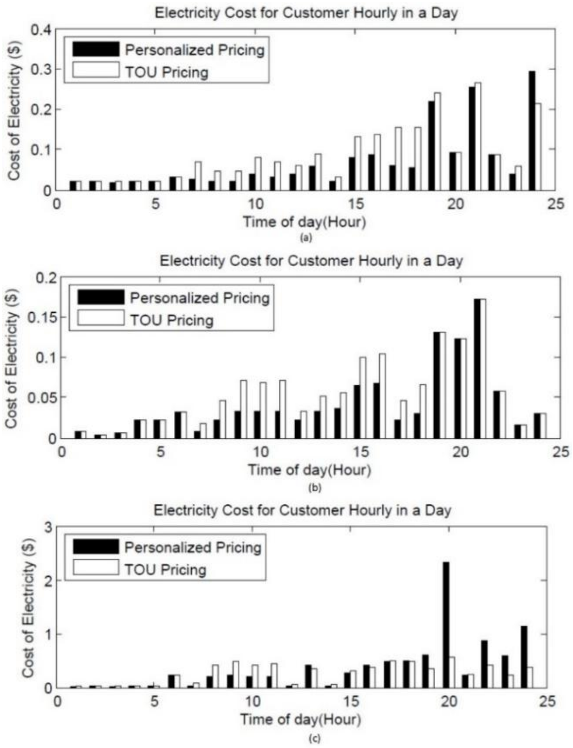

Figure 3. Customer's hourly electricity cost in a day a) "usual" customer b) "good-behavior" customer and c) "bad-behavior" customer.

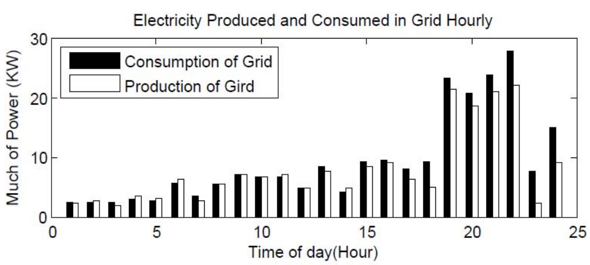

Figure 4. Electricity demand and supply in a day.

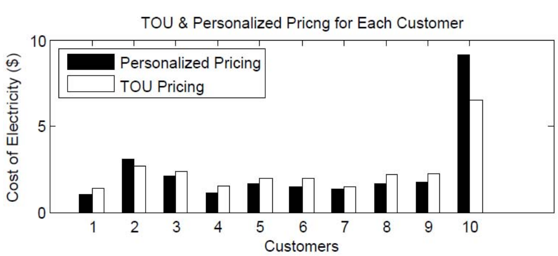

Figure 5. The total cost of two types of pricing: TOU and personalized pricing.

IV. CONCLUSION

In this paper we proposed a new pricing method to make positive incentives in customers to reduce their consumption levels. In our method, at first, we allocate specific amount of electricity to each customer at each hour during a day and then determine their consumption levels by using personolized pricing function to calculate the corresponding costs at the end of each period.Indeed, our proposed model defines a new way to convince customers to reduce their consumption levels at peak hours.This happens due to the fact that in our method if you increase your demand levels beyond your allocated limits, your costs will be increased respectively. Although our pricing function calculate lower costs for customers who consume less than their allocated power. Those customers who consume more power than their share and have direct effect on peak hours in the grid, should pay more than the others.For future works we can also change our price function to change ways of calculating costs. Also we could add other incentive programs to increase saving electricity.

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