DEMAND SIDE MANAGEMENT CONTROLLING WITH PERSONALIZED PRICING METHOD

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ABSTRACT

Among many key subjects in smart grid technology, Demand Side Management is one of the common and popular subjects that interest researchers in controlling and monitoring customers' activities. In reality, Demand Side Management depends on scheduling and policy of the utility companies to impress customers' consumption to change their consumption patterns with the goal of balancing the load of the electricity network, especially on peak-time hours. Pricing methods are so popular among the issues of Demand Side Management to control customers' consumptions. By determining various articles in pricing field, one of the most interesting methods is real-time pricing. However, in this paper, we proposed a personalized pricing scheme which means that it is using customers' real-time consuming data to produce a real-time price for each of them. In this method, the pricing was not only affected by the total consumption of the grid but also depends on personal consumption of each customer. It means that according to the consumption of each customer at the moment, the price will change individually for them. Our proposed model consists of a new device that must be placed on the smart meter and calculate the new price by examining the amount of customer's consumption at the moment. The price at each customer's smart meter will be calculated with both prices of the electricity network (that is received from utility power when the load of the network changed) and a price which is calculated by the smart meter's device. In personalized pricing for calculating the price, we are considering on behavioural and household features of each customer, his/her consumption pattern, consumption history and some other features that have an effect on analysing the price for each of them.

INTRODUCTION

Real-time pricing is a variable pricing scheme that changes the price of network whenever the total consumption is changed. The way of choosing and changing the price depends on the whole customers' electricity consumption at the moment. As was mentioned, the price will be affected by the total electricity consumption, but for having an efficient and fair pricing scheme, we have to mention each customer's consumption pattern.

Therefore in this paper, we are going to use a new method of pricing that is useful for utility companies to encourage customers to change their consumption patterns and reduce their power consumption that will result in cost reduction. Also, we proposed a new infrastructure for transferring the data that are necessary in real-time pricing methods.

In many related works, the problem of most power grids is to find a suitable mechanism of pricing that is fair for both customers and power utilities. All researches were done on preparing a new method of pricing by considering the grid total power consumption [1].

Dynamic pricing method is a kind of real-time method, but with a difference, that it can change the price of the grid considering the customers' consumption changes. One of the popular methods of pricing is Time-Of-Use (TOU). This method was designed to allocate a unique price to all customers at different time slots of a day [2]. Some kinds of methods want to encourage customers to reduce their consumptions, therefore, they use cost functions and solutions to allocate good behaviour customers a rebate to make an incentive for reducing their consumptions especially during peak hours [3]. One of the important issues for estimating a fair price for the grid is to consider the load of power consumptions. It means that the load of the grid will affect the price and the amount of price will affect power consumptions [4]. Therefore, we have bidirectional effect. In addition, for reaching the highest gain and power reduction, customers can change their behavioural patterns of power consumptions.

As a result, our proposed model is using an individual method of pricing for each customer to determine their power consumptions and allocate them a unique price by considering their allocated power. In [4], we represent a new cost function and divide customers into two groups of consumption. Also, we allocate customers a unique amount of power by considering their household features for each time slot. Thus, we want to use Personalized Pricing and use optimization problem for allocating an optimal amount of power to the customers.

One of the main goal of this paper is proposing an efficient infrastructure for the Personalized Pricing that is consist of a new generation of smart meters with the ability to process power consumption data. In [5], [6] based on their proposed model, they add some modules to their proposed smart meter to be compatible with the grid infrastructure. Another important subject in smart grid infrastructure is the big amount of data that must be transferred between customers and utility powers. These data contains customers consumption per time slot, customers' costs and so on, depends on the grid structure. The huge amount of data will make overload in the grid communication. Therefore, in a network communication with the need of transferring huge amount of data, delay and packet loss may happen for them [7],[8]. Thus, the subject of Big Data appeared in smart grids [9]. In dynamic pricing methods for using real-time approaches, processing a huge amount of customers' data for each time slot of a day will reduce the ability of processing information. To determine [5], [10], we find out that the best way for reducing the load of the grid is to use distribution network communication for delivering data to customers' sides. In addition, we decide to add a Pricing Logic Unit (PLU) to the existent smart meters to give them the ability to control customer's consumption.

The paper is organized as follows. Section 2 illustrates system model. Section 3 presents the simulation results and finally section 4 concludes the paper.

SYSTEM MODEL

In our proposed method, we decide to use an individual pricing model for customers at each time slots by considering a distributed infrastructure and a new logical unit in customers' smart meters for calculating their costs of power consumptions. In addition, we want to emit the process of calculating customers' cost from utility power and put this ability in customers' side. Also, it is sensible that power utility should send a base information to the customers' side related to their cost function. The cost function that we use in our smart meter is Personalized Pricing that is used for calculating customers' costs in real-time individual power consumptions. We consider that we have a power grid with N customers and divide 24 hours of a day into H time slots. Therefore, i illustrates the number of customers that i∈N and h shows the number of time slot h∈H.

Power Allocation

Power utilities always should estimate the amount of power that their customers need to consume. Therefore, they use prediction solutions for estimating customers' demand. For allocating power, some household features have a direct effect on customers' consumptions such as home size, number of occupants, number of windows in home and so on [11]. As we said in [4] we use (1) for finding customers' share of power consumption from produced power. α_i is a coefficient that presents the share of customer i from the amount of power generated in the grid. Also, the sum of α_i for all customers will be equal to one ($0 < \alpha_i < 1, \quad \sum_{i=1}^{N} \alpha_i = 1$).

$$\alpha_i = \sum_{j=1}^{F} \mu_j \times a_{j,i} \tag{1}$$

Equation (1) shows a sum of multiplication of household feature $a_{j,i}$ which presents the amount of household feature j of customer i and μ_j shows the amount of effects each household has on power allocation. Also, F is the number of household features. Then, for optimizing μ_j, we use (2) and w_j is a constant that has been reached from [10].

$$Maximaize \ \sum_{j=1}^{F} w_j \times \mu_j \tag{2}$$

$$subject\ to.$$

$$\mu_j > 0, \quad \sum_{j=1}^{F} \mu_j = 1, \quad \forall j \in k$$

After the optimization, α_i will be calculated and used for allocating power to each customer with (3). G_s^h represents total power generated at time slot h and p_i^h illustrates power allocated to customer i in time slot h.

$$p_i^h = \alpha_i \times G_s^h \tag{3}$$

Personalized Pricing

Our cost function was illustrated in [12]. Therefore, we use it to calculate customers' cost of power consumptions. At the end of each time slot, customers could be informed of their total consumption and the cost of last time slot with their smart meters. The information will help them to decide about their next time slot power consumption and reduce their costs. On the other hand, the main goal of this paper is to inform customers about the prices of the grid at each time slot and show the cost of power to each customer. Therefore, this method will help them to schedule their power consumptions to reduce their costs for the next time slot.

e_i^h shows the amount of power customer i consumes at time slot h and $e_i = \{e_i^1, e_i^2, \dots, e_i^H\}$ is a vector of customer i power consumptions. G_s is the total amount of power estimated for customers' consumption in a day and is equal to $G_s = \{G_s^1, G_s^2, \dots, G_s^H\}$.

$$Cost(e_i^h) = \begin{cases} c_1^h \times e_i^h & if\ e_s^h \le G_s^h \\ c_1^h \times e_i^h & if\ e_s^h > G_s^h\ and\ e_i^h \le p_i^h \\ c_1^h \times p_i^h + c_2^h \times (e_i^h - p_i^h)^2 & if\ e_s^h > G_s^h\ and\ e_i^h > p_i^h \end{cases} \tag{4}$$

For calculating customers' cost, (4) is used to represent a difference between customers who consume lower than their allocated power ($e_i^h \le p_i^h$) and customers who consume more ($e_i^h > p_i^h$). But, the difference when the total power consumption will be more than allocated power at each time slot is sensible ($e_s^h > G_s^h$). It means that at this moment the grid goes to a peak hour consumption and their behavioral pattern will be affect their costs.

We consider that $c_1^h < c_2^h$ and c_1^h is a base and constant price of power consumption. In contrast, c_2^h is a variable price that will change when the grid produces extra power or in other words peak-time happens for the grid.

Infrastructure

Another goal of this paper is to represent a new communication infrastructure which is suitable for Personalized Pricing method. In new established infrastructure because of the limited access to the sources and high bandwidth, researchers intended to present a suitable infrastructure for our proposed dynamic pricing model.

In our proposed model, we consider using a distributed and packet-based infrastructure for reducing and exchanging the huge amount of data that must be sent to all customers. All residential customers are linked to data and power line that fig. 1 will show the infrastructure of

our proposed model. Our Personalized Pricing model uses a bidirectional communication. Each smart meter has an identification code that is used for being identified in the grid and send or receive their own packets. Thus, this solution will reduce the traffic of network and the amount of data should be sent.
For personalizing our cost function, we need to send some special data to the specific customers individually. Therefore, we proposed a new structure of packets that is used smart meter ID. Smart meter ID is a unique number that will be allocated to each of them. The packet base model will contain p_i^h, the amount of power that is allocated to the customer i at time slot h, e_s^h, the total amount of power the grid customers consume at time slot h. Peak-hour is only a bit flag, when the total consumption of the grid rises up more than the produced power then this flag will equal to 1 and c_2^h segment will contain the extra power consumption price. Also, if Peak-hour flag is being equal to zero, then, c_2^h will be equaled to zero too. In addition, the smart meters should send some data such as the amount of power consumed and the cost to the power utility when its calculation for the customers cost finished. Also, some data will be transmitted to the smart meters from utility power for PLU calculations at the end of each time slots.

Smart Meter

A smart meter is an intelligent device for measuring the amount of customer's power consumption and then send the data to the power utility using communication lines [13]. Smart meters are an important part of smart grid infrastructure that is located in customers' home side. The reason for using this kind of meter is the ability to send real-time data to decide about the demand of customers in the shortest time.

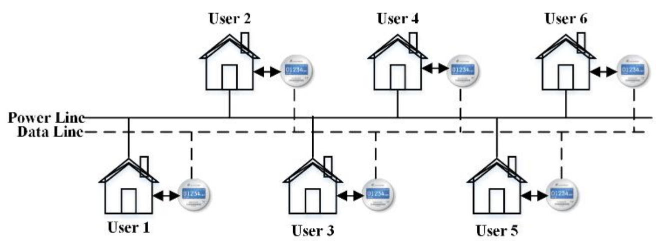


Figure 1. Power and data line infrastructure for our proposed model.

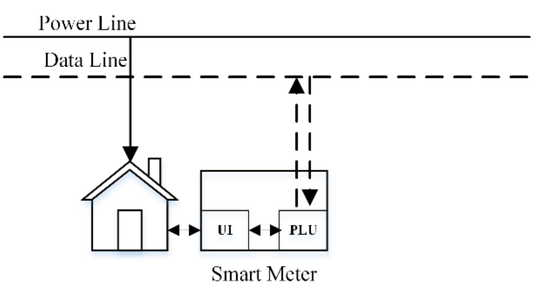


Figure 2. A sight of proposed smart meter.

The new generation of smart meters is equipped with high-speed communication infrastructure for transferring data among customers and power utilities. In our proposed model, we decide to design a new smart meter which is compatible with our model that have the ability to process customer's power consumption and compute his/her cost using Personalized Pricing method for each time slot. Figure 2 illustrates our proposed smart meter.

Pricing Logical Unit (PLU) is a mathematical computational unit that should monitor customer's consumption and calculates the cost of each time slot using Personalized Pricing. Also, the main goal of designing the smart meter is to reduce the load of mathematical computation. In addition, this smart meter has a User Interface (UI) for customers to interact with it and see the diagram of their power consumptions and their costs for each time slot.
PLU is programmed to calculate customer's cost by considering the cost function presented above (4). Therefore, this unit's duty is to calculate customer's cost with (4). For calculating cost for each time slot, smart meters need some data. As we present above, the total amount of power consumptions, allocated power to each customer, base price, variable price, and being aware of peak hours on the grid that has a direct effect on costs are proposed.
Therefore, the smart meter will help customers to monitor their consumptions and being aware of peak hours. Also, at the end of each time slot, customers can decide to change their behavioural patterns in consuming power for the next time slot, when they see their cost and power consumption on UI.
Security is another important subject in our proposed model that we will not allowed customers to change their consumption data. In other words, they are not able to send wrong data and cheat. At the end of each time slot customers' power consumption and their costs will be sent to power utility side. Then, at the end of the day, power utility will calculate their costs, and check all the customers' consumptions and compare with their costs they reported.

SIMULATION RESULT

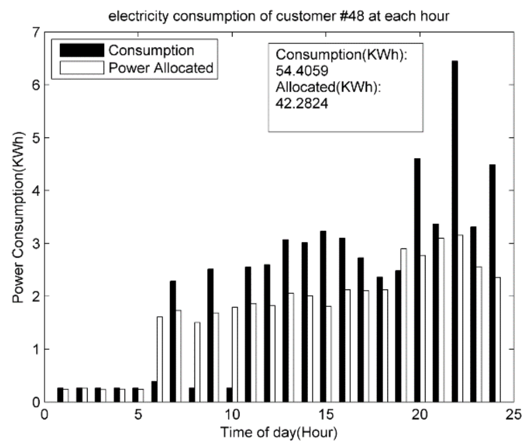
We use Matlab software for simulating 50 customers of a residential region. Each customer has some electrical appliances that we use the data of statistical center of Iran for simulating their consumptions. First, we consider that the grid produces G_s^h for each time slot. Also, for calculating customers' consumptions of a grid we can use load prediction models for estimating their consumptions [14]. But, we consider that the amount of power generated for time slot h is equal to customers' demand with an amount of ΔG_s^h lower or higher. We allocate customers a specific amount of power for each time slot at the start of a day. Therefore, it will help them to schedule their power consumptions to consume lower than allocated power.

We simulate customers' consumption in 24-time slots of a day. Also, we compare our proposed model with other pricing models such as TOU and a quadratic cost function. Quadratic cost function was illustrated in [5] and is a function that power utilities use it for calculating power generation's costs. Equation (5) will show the quadratic cost function.

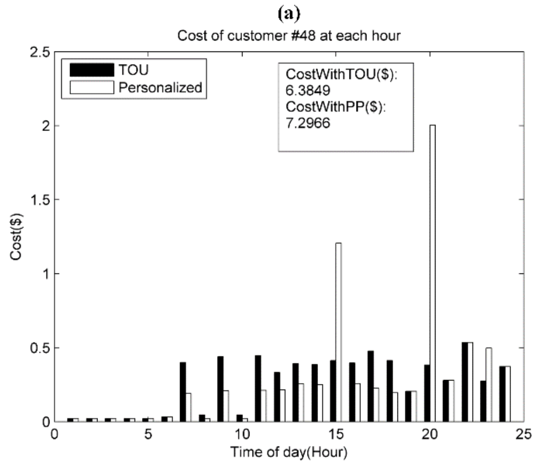
$$C_h(e_s^h) = a_h {e_s^h}^2 + b_h e_s^h + c_h \qquad (5)$$

In (5), $a_h > 0$ and $b_h, c_h \geq 0$. We consider that $b_h, c_h = 0$ and a_h will be changed with the amount of power generation in a day.

Figure 3 illustrates customer #48 that his/her total consumption is more than the allocated power. We represent that the customer's cost in Personalized Pricing model is more than TOU especially when they consume more than their allocated power. Also, Figure 4 represents fluctuations in power consumptions and costs for all 50 customers in a day.



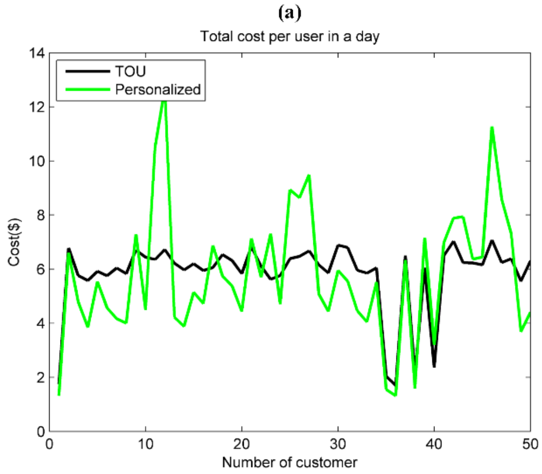
(a)



(b)

Figure 3. Customer #48 consumptions and costs in a day.

(a)



(b)

Figure 4. All customers' power consumptions and costs in a day.

In comparison, between TOU and Personalized Pricing, the latter causes that customers who consume more than their allocated power, their costs will be more than TOU pricing and we believe that when a customer faces with high price he/she may encourage to reduce his/her consumption for the next time slot. On the other hand, the proposed model can make incentive between customers whose consumptions are lower than their allocated power to always consume lower or equal to their allocated power.

To compare the grid's costs of power generation in our proposed model with two other existing cost function, fig. 5 represents power generations' costs for each time slots. Peak hours in TOU and quadratic cost function are defined as fixed intervals (for example from 5 pm to 7 pm). Therefore, they will increase the grid's costs of power generations for all peak hours. While, the grid's power consumptions at defined peak hours may not be more than the power generated. Thus, their cost functions cause an unfair situation in calculating the grid's costs. But, in Personalized Pricing, the calculation of grid's costs depends on customers' power consumptions' patterns which will cause peak-time at different time slots. In additions, it shows that our cost function is fair for calculating the grid's costs in comparison with quadratic and TOU.

CONCLUSION

From our simulation results, we understand that our proposed infrastructure will emit the high processing of the big amount of data for each time slot at the utility side. The existing communication networks use central data processing for calculating customers' costs. Therefore, they need high-speed bandwidth infrastructure and powerful processors for the calculations. But in our model, we use a distributed infrastructure with a common data line for transferring data between the utility company and customers' smart meters.

Also, our proposed cost function in comparison with TOU is an incentive-based function that tries to encourage customers to reduce their consumptions by increasing their costs, especially at peak hours. In addition, Personalized Pricing method decides to create an incentive for customers' to reduce their consumptions and change their power consumption scheduling for the next time slot to reduce their costs. For calculating the grid's power generations' costs, our proposed model calculate the fair costs in comparison with the quadratic function and TOU. Also, the peak-time intervals will be defined by considering the grid's consumptions.

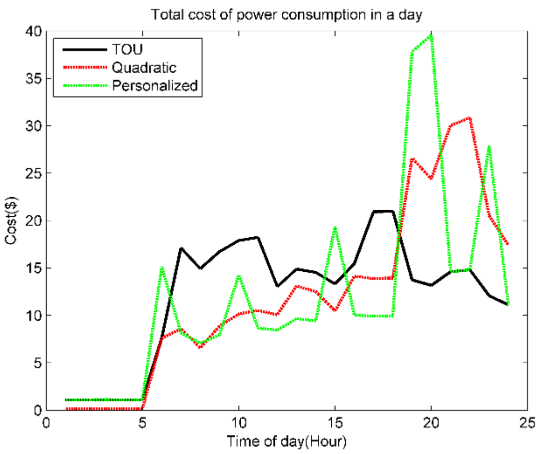


Figure 5. The grid's cost of power generation at each time slot of a day

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