Dynamic Pricing with Fuzzy Logic for Smart Grids

Hassan Mahmood[1], Muneeba Fatima[2]

Abstract*—With the rapid increase in electrical devices like electric cars, the demand of electricity is increasing. It becomes difficult for grids and utility companies to meet this higher demand. Meeting the demand increases the production cost while consumers pay the fix amount. Dynamic Pricing is a type of DSM (Demand Side Management). DSM is any activity which can impress the power consumption of a consumer. This is usually done by utility companies by introducing policies like pricing schemes. Some currently used pricing methods involve Real-Time Pricing (RTP) and Time of Use (TOU). Real Time Pricing calculates prices in real time based on grid's demand level. In this paper, a new pricing method is proposed that uses grid's real time consumption data and also considers consumer's consumption data to define real time prices. Our approach introduces a habit factor to keep track of the consumer's usage history. Some approaches use Machine Learning and Artificial Intelligence to learn about the customer but it requires a lot of computation to train these models and to process the data. Our solution uses the simplest form to cater consumer behavior, through fuzzy variable which reflects the consumer habit of using electricity. The major purpose of the newly introduced fuzzy variable is to penalize the repetitive threshold exceeding behavior, as compared to the older approach, which costs same factor every time the usage exceeds the allotted power. Our results show that our pricing model penalizes the bad behavior and a good behavior reduces the impact of bad behavior with time.

I. Introduction

Rising electricity consumption and inadequate pricing strategies are increasingly becoming the cause of worrying for power houses and electricity distribution units. Where previously, power consumption was not so much to require a dynamic pricing strategy, it is now increasingly rising, and producers and distributors have to come up with strategies not just to dynamically price power units but also make electricity usage more efficient and if possible to reduce it so maximum consumers can benefit without burning a hole in their pocket.

Smart grids have been under discussion for the past few years in discourses about dynamic pricing. Our paper aims to solve the problem of static pricing and increasing consumption of power using the solution that is aided by smart grids. Smart grids essentially focus on dividing the power consumption times into three main categories: off load, normal load and high-load. These time categories increase in usage of electricity from left to right. The solution essentially proposes that, using a smart grid, units consumed during high-load period should be charged more than those used during off and normal-load periods. This will not only deter users from using excessive electricity during times of high power demand but will also encourage them to distribute their usage throughout the day, so no period is stressed by power demand. This will ensure fair distribution of power to all users and ease in distribution of power for distributors.

The paper first analyses some of the papers that were studied to come up with our solution. It then continues to present our methodology and solution. And in the end, it explains the potential for future work and research.

II. Literature Review

Various models and algorithms have been proposed to implement Dynamic Pricing method in smart grids. We will go through some of the important algorithms and models.

M. H. Yaghmaee proposed Personalized Pricing approach[1] in which a weighted average of six features or factors is determined to allocate power and the customer is penalized for exceeding the allocated power during peak hours. Although, it is a better alternate of other pricing models like TOU but it does not provide any flexibility in terms of electricity usage provided the same number of household features. Another problem with this approach is the use of variables with values 0 to 1 in quadratic equation. The square of a value between 0 and 1 will give a smaller value, hence this approach does not correctly calculate the price.

Unit pricing based on usage during different times has been becoming increasingly popular in the smart grid area of research. This method of pricing however has some problems associated with it that need to be addressed. This method is not truly dynamic in the sense that the peak and off times along with their unit prices are pre-defined. Rates and usages are not calculated at runtime but are pre-programmed. Liang et al., in their paper [2], have proposed a solution to this problem. The new dynamic pricing strategy that they introduce allows usage records to be updated dynamically while preserving the privacy of the user. In accordance with the capacity of the local power grid, a usage limit is defined. A usage pricing function, which may be different for different communities based on their usage is then introduced. The customers report their electricity usage to the community gateway and mix it with a secret variable for privacy preservation. The gateway is then able to get a report of the whole communitys power consumption at a certain time. The utility company, which knows the secret variable of each user, removes the variables from the report and generates a bill for each customer depending on the power usage of the whole community.

Abaza et al. identified the problem that though most smart grid based systems were looking to optimize the pricing of the power units, they disregarded the users reaction to change in power consumption load. The consumers response is missing from mainstream discourse on smart grids. This is the problem that their paper [3] aims to tackle. The paper aims to shift the load from peak times to off-times to balance the need of power in consumers. In addition to this, the paper also aims to reduce overall energy consumption in consumers; they aim to do this by introducing and encouraging the use of more power efficient electronic appliances and thus consequently reducing the overall power consumption.

Raza Khan et al. aim [4] to solve the problem of inadequate pricing strategies by using smart grid too. They propose the usage of smart grid for dynamic pricing to change the users needs for power. In addition to this they also suggest the usage of smart grid for forecasting the load of power for certain time periods. Load Forecasting using this strategy is divided into three categories: Short term LF from hours up to a week, Medium term LF for weekly, monthly and yearly basis and long term LF for forecasting the load of up to fifty years. Forecasting the demand is crucial in the power sector to adequately plan and prepare for the coming years. This paper however fails to explain how demand will be managed in the present and primarily focuses on the future.

Kim et al. [5] propose a paper in which the customers demand for electricity, the rate generation for each unit and energy consumption, all are dynamic contrary to previous work where only the rate per unit is dynamic. Similarly, Zheng et al. [6] in their paper propose the usage of artificial neural networks along with smart grids. Artificial neural networks generate patterns based on similarities form past experiences. These patterns then help determine the peak and off-load hours based on past consumer usage of electricity during a certain hour of the day. Other works use game theory [7] to evaluate pricing models with the results demonstrating that RTP maximizes peak load reduction by 10% for residential sector and 5% for commercial sector.

III. System Model

Our model improves existing dP models with some additions and is inspired by the Personalized Pricing approach[1].

A. Naive Approach

A naive approach is to calculate the unit price for the whole network based on power consumption. As in [2], the price is calculated based on the Grid Power Supply and total power consumption of the whole network. So, essentially, it caters only the supply side. With this approach, all consumers will have same price per unit, irrespective of their usage. On the other hand, this is a good technique to limit the consumer's allowable usage.

$$\text{Price per KWh} = p_{i,h} \cdot c_{1,h} + (e_{i,h} - p_{i,h})^2 \cdot c_{2,h}$$

Where,

$$\text{Allocated Power Per Consumer} \quad p_{i,h} = \frac{G_{s,h}}{n}$$
$$\text{Power Usage Per Consumer} \quad e_{i,h} = \frac{e_{s,h}}{n}$$

$G_{s,h}$: Grid Power Supply per hour
$e_{s,h}$: Network Power Consumption per hour
$e_{i,h}$: Power Consumption per hour by Consumer i
$p_{i,h}$: Power Allocated per hour to Consumer i
$c_{1,h}$: Fix Cost per hour if $G_{s,h} \leq e_{s,h}$
$c_{2,h}$: Fix Cost per hour if $G_{s,h} > e_{s,h}$

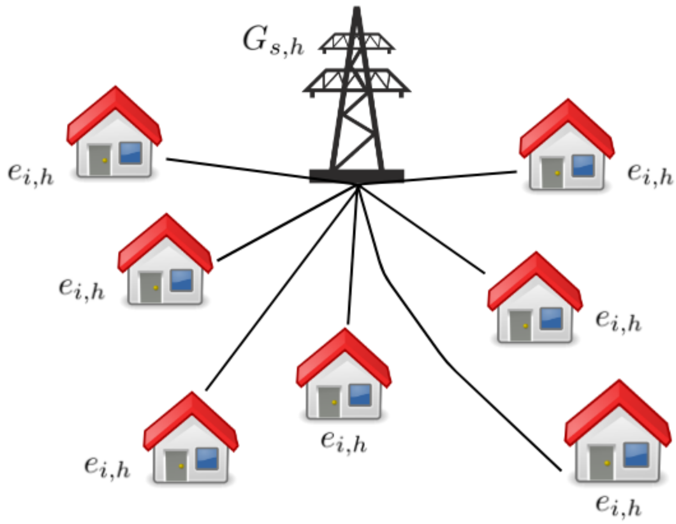


Fig. 1: Grid Network

B. Power Allocation

Our model allocates power based on the household features and considers the usage history while determining the cost for each consumer.

For a region covered by a grid, suppose there are N consumers. For each of the consumer, a power factor ρ will be calculated based on household features which will determine the power to be allocated.

Total 6 features are chosen which affect the electricity consumption the most. Each feature is represented as f and the total normalized power ρ_i will represent the power allocated to consumer i.

$$\rho_i = \sum_{j=1}^{6} w_j \cdot f_j$$

Where weights are on a scale of 0 to 1. After calculating power factors for all consumers, we normalize these factors so that:

$$\sum_{i=1}^{N} \rho_i = 1$$

Which means that the total allocated power must be equal to the grid supply power. Then, each power factor will show the percentage of total grid energy, a consumer is using.

ρ_i is recalculated when there is a significant change in the features of a consumer.

C. Our Contribution

In our model, prices are calculated for each consumer individually based on some household features for the profit of both, consumers and utility companies. These household features are a good predictor of consumer's demand. Through these features, we will allot a power factor to each consumer and that power factor will be a threshold for electricity price. In other words, consumer using power below this threshold will be charged less while those crossing this threshold will be charged as per the difference between usage and alloted power using a quadratic function.

Data will be collected from consumers at specific time intervals and all the calculations will be done to reallocate the power to each consumer for any significant change.

In the proposed model, we introduce a fuzzy variable to determine the behavior of a consumer as good or bad. This variable changes value on a scale of 0 to 1 according to the usage of consumer. The purpose is to keep track of electricity usage of a consumer. A value close to 0 shows good behavior and a value close to 1 shows bad behavior.

b_i is behavior of i^{th} Consumer. The variable value caters current behavior and previous history to calculate the factor by which the consumer will be penalized.

$$b_i = 0.8 \times b_i + 0.2 \times k$$

Where,

$$k = \frac{e_{i,h} - 1}{p_{i,h}} \qquad k \in \mathbb{N}$$

The value of k is an integer value and it is used to determine if the current power usage is within the allocated range. It will have a value of 0 if the usage is within range and a value of 1 if the usage exceeds the alloted threshold. So the price will be calculated as below:

$$cost = \begin{cases} e_{i,h} \cdot c_{1,h} & e_{s,h} \leq G_{s,h} \\ e_{i,h} \cdot c_{1,h} & e_{s,h} > G_{s,h} \text{ and } e_{i,h} \leq p_{i,h} \\ p_{i,h} \cdot c_{1,h} + (e_{i,h} - p_{i,h})^2 \cdot c_{2,h} \cdot (1 + b_i) & \\ & e_{s,h} > G_{s,h} \text{ and } e_{i,h} \leq p_{i,h} \end{cases}$$

The flowchart of our proposed model is shown in figure 2.

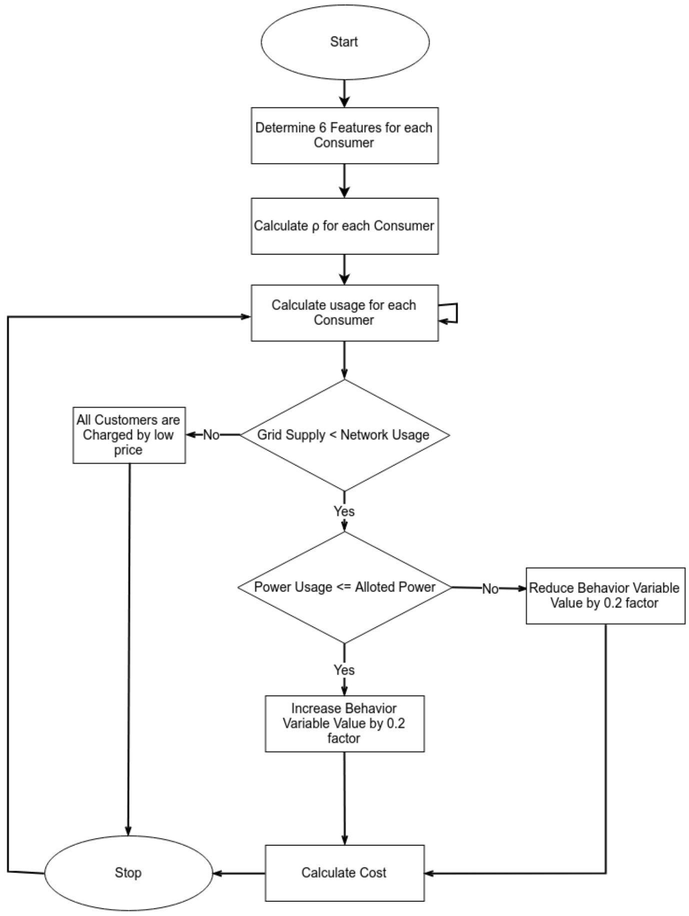


Fig. 2: Model Flowchart

IV. Simulation

As seen from the simulation in figure 3, the model penalizes more to consumers with frequent 'bad' behavior. While for the 'good' behavior, it lessens the impact of bad behavior. Once, a consumer is determined to fully have a good behavior, the model works the same as old model.

A. Simulation Methodology

For simulation, we randomly alloted power to each user and randomly generated the usage. Then two different methods were applied to calculate the cost. The old method which does not cater the history of the consumer is compared with the proposed one. The simulation was run in four iterations with different input data each time. Two of the input data stream were randomly generated while the other two were generated by ourselves to visualize the results of proper working of the model.

B. Simulation Results

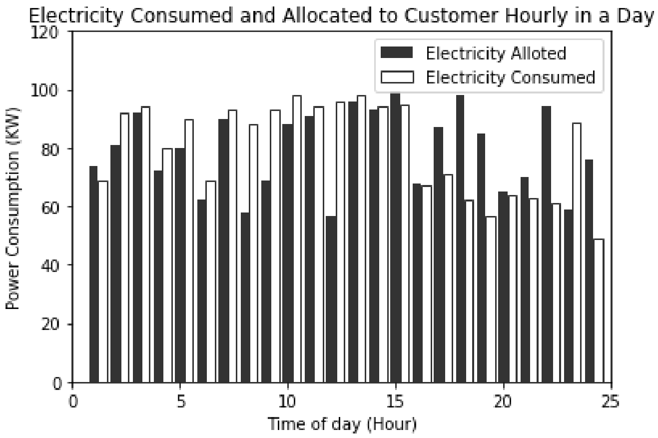
The figure 3a and figure 3b show electricity consumption and the cost calculated by two different methods, respectively. In this iteration, data is randomly generated. Now, our proposed model first computes the same cost as the old model but as the consumer behaves bad multiple times, our model penalizes with more cost.

In figure 4a and figure 4b, the proposed model lessens the impact of bad behavior when the consumer has good behavior. So in these figures, we can notice that the behavior oscillates between good and bad and the resulting cost involves bad habit factor.

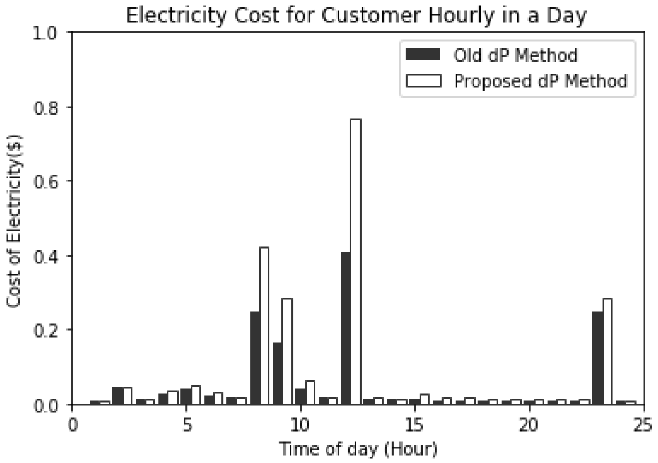
In figure 3c and figure 3d, a constant bad behavior is depicted. So the model iteratively increases the bad habit factor and penalizes more until a limit is reached.

In figure 4c and figure 4d, first the consumer exceeds the usage limit, then remains in the limit and lastly, exceeds the usage limit.

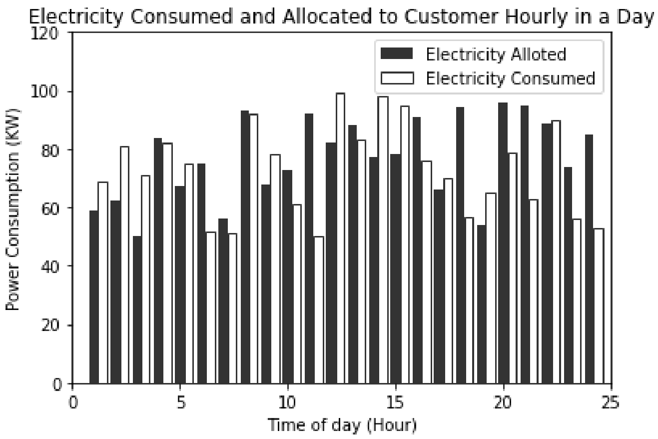
It is vivid from the results that our proposed method works better in terms of tracking the consumer behavior.



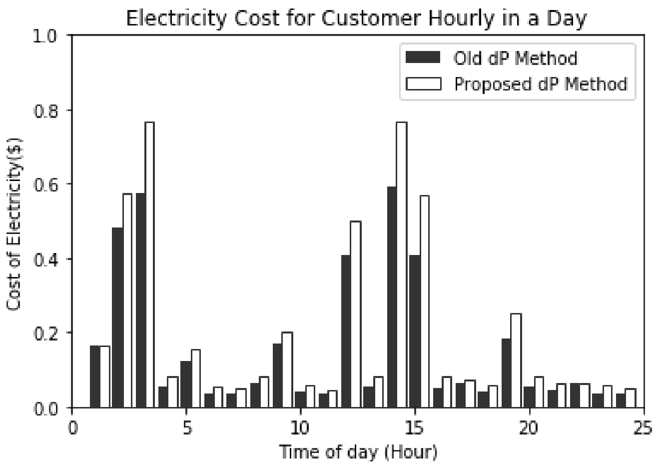
(a) Consumption Plot



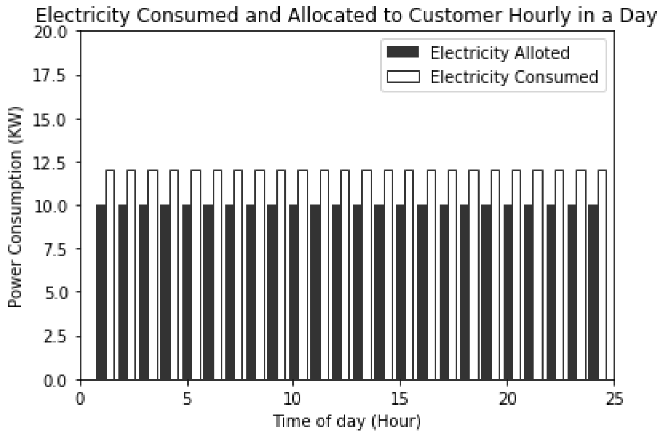
(b) Cost Plot



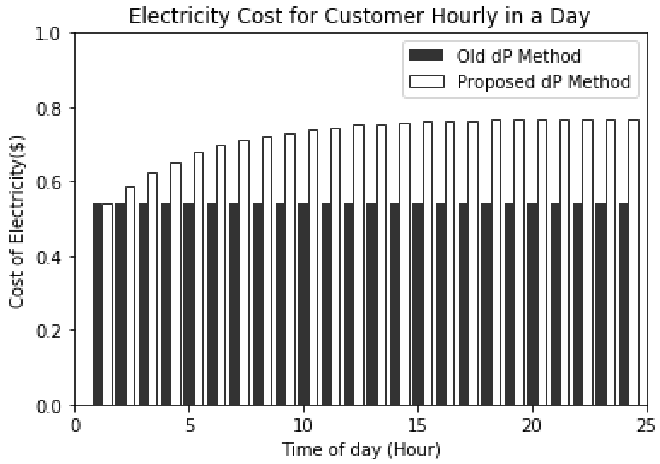
(c) Consumption Plot



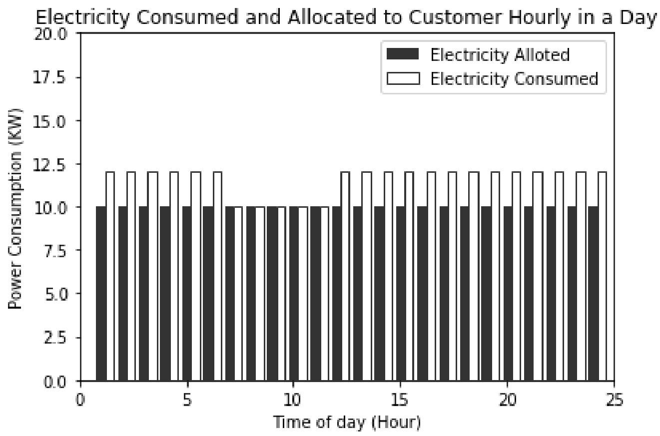
(d) Cost Plot



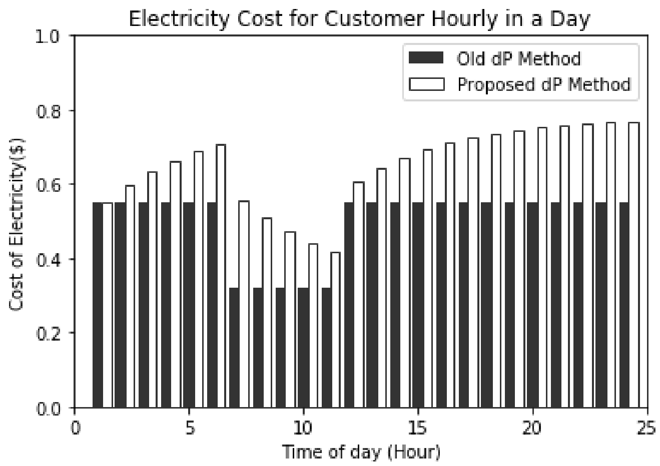
(a) Cost Plot



(b) Cost Plot



(c) Cost Plot



(d) Cost Plot

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Fig. 3: Simulation Results

V. Conclusion

In this paper, we proposed a new dynamic pricing model which caters the supplier side and the consumer side during electricity price computation. Our model keeps track of a consumer habit using fuzzy variable. A certain power threshold is allocated to each consumer based on some household features. The power usage above or below the allocated threshold determines the cost of electricity. Our model convinces the customer to reduce the power usage during peak hours and makes them avoid exceeding the limit by penalizing them and categorizing their behavior as bad. Exceeding the limit increases the cost price of electricity and repeating the behavior penalizes polynomially. For future work, we can introduce smoothing factors to the fuzzy variable and can make it more robust.

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