An Analysis of Profits and Savings in Generation Cost for Different Dynamic Pricing Schemes

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***Abstract*—Dynamic pricing in electrical systems is a promising tool that could be used in future power grids to modify the overall shape of the daily demand. This can have enormous benefits for utility companies, which can use different demand shaping techniques to modify the shape of the demand in ways that can reduce the overall cost of generation or increase their revenue. By appropriately introducing real-time pricing schemes, utility companies can effectively reshape the daily load profile, to reduce the peak load or fill the early morning demand valleys. In this paper, two different dynamic pricing schemes are evaluated in terms of the way revenue is procured. While in some cases, revenue is increased by the simple reduction in generation cost; in other cases, the higher price premiums yield an increased revenue to the utility companies. Results show that different schemes, as well as different customer flexibility and awareness levels, can significantly contribute to the amount and type of revenue utility companies can procure.**

***Index Terms*—Dynamic Pricing, Demand Clipping, Percentage Reduction.**

I. Introduction

Dynamic pricing in Smart Grids has the ability to modify the shape of the demand in ways that are beneficial to the utility companies and can provide a more reliable, stable, and efficient grid operation.

By providing the right amount of motivation, customers can be encouraged to shift their unnecessary loads into the times of the day when the overall loading conditions are light, which has the additional effect of reducing the demand at peak hours. The overall effect would be a less-varying demand curve, which will reduce the overall cost of generation.

Typically, this is achieved by allowing the prices of electricity to vary throughout the day, such that the prices are higher during high demand periods, and lower during lower demand, thus encouraging customers to shift their loads. However, not all customers are equally aware of the notion of dynamic pricing and how it can be used to their advantage. Moreover, some customers do not necessarily have enough flexibility in their schedules to allow for a change in their electric usage habits causing them to resist the temptation of modifying their consumption patterns even if it comes at an extra cost on their electric bill.

The work in [1] and [2] discussed the notions of flexibility, awareness, and motivation in great detail, and provided an analysis of possible scenarios for customer behavior under various dynamic prices schemes. In addition, such schemes were optimized to get the best possible result from the utility perspective in terms of the overall reduction in generation cost or the overall profit obtained.

Meanwhile, this paper evaluates the effect of dynamic pricing on the savings in generation cost and overall profits from the perspective of utility companies. The paper builds on the work presented in [1] and [2] by providing financial analysis of a number of interesting cases, which represent different dynamic pricing strategies. This work also outlines the properties of these strategies by pointing out their differences and impact on customer behavior.

It is suggested that the overall goal of dynamic pricing is to reduce the variation in demand and achieve a cost-efficient power generation that maximizes the electric output for a fixed amount of fuel. However, utility companies might be tempted to maximize their own profits rather than the efficiency of generation, which may lead to two conflicting strategies in terms of dynamic pricing.

Another related aspect that is worth investigating is related to the nature of the profits (or cost savings) that utilities achieve using dynamic pricing. For example, one might think that the savings obtained by reducing the demand during peak hours are quite significant. On the other hand, the added profits achieved by higher prices during peak hours can add a significant overall profit to the utility.

In this paper, the effects of different dynamic pricing strategies and the variations they produce in terms of shaping the demand curve are highlighted, with a focus on the financial aspects of such pricing schemes, and the contributions of cost-saving versus the added profits of high prices on the overall earnings of the utility companies.

A number of related studies have been found in the literature, which focuses on such aspects as finding optimal pricing strategies, which help the customers save more on electricity, while others focused on reducing the cost of generation. Other studies, focused on evaluating the efficiencies of the existing pricing strategies.

For example, the work in [3] presents a framework for evaluating the economic efficiency of different electricity pricing schemes; however, the focus is on pricing schemes that are dependent on the location of demand and the distance traveled by electric power, rather than demand-based real-time pricing. The authors of [4] compare the cost of generation under different dynamic pricing schemes showing the difference in cost between them. The focus is on pricing schemes such as Time of Use (ToU), and Minimax schemes, with the overall objective being to flatten the demand and reduce the cost of generation.

Several papers focus on developing pricing strategies that take into consideration various aspects such as the cost of generation, and shape of demand, among other factors. For example, in [5] the author presents an optimization algorithm that aims to minimize the cost of energy bought from the grid, while also maximizing the cost of energy sold to the grid. The algorithm makes use of different dynamic pricing schemes such as ToU and Feed-in tariffs, and also makes use of energy storage systems such as batteries to consume (or store) power during low demand periods and supply it back during high demand.

In [6], the generation cost function is taken in addition to other parameters such as customer satisfaction index and the safe operation of the grid. As such, a multi-objective function is introduced in producing a real-time pricing scheme. The work in [7] presents an algorithm for the dispatch of energy sources with the target goal of reducing energy consumption and increase our dependence on clean energy. Both short-term and long-term algorithms are presented.

In [8], the authors present an algorithm for real-time pricing that takes into consideration savings on the user side and utility side as well, such that it reduces the peak-to-average ratio, while also provide savings on both sides. The work in [9] presents a closed-loop pricing strategy, which takes into account the randomness of customer demand and their ability to modify it using appropriate pricing strategies.

The studies that actually focused on studying the savings were very few. In [10], the authors present a study of customer behavior in a dynamic pricing environment with a focus on the amount of savings that customers can achieve should they participate in dynamic pricing schemes. A key finding is that high-paying customers achieve higher savings (up to 31% annually) than low-paying customers, who typically only achieve savings of less than 1%. The authors of [11] present a study for industrial customer savings under ToU and Real-Time Pricing (RTP) schemes. Different users with different levels of flexibility and usage patterns experienced different amounts of savings and in some cases, also experienced financial losses.

This work is different, as it focuses on evaluating the effects of different pricing strategies directly on the savings in the cost of generation, and the profits of utility companies. In fact, this work focuses on the effects of real-time pricing on the utility companies' side rather than the customers' side.

The rest of the paper is organized as follows, section II details the basis of the dynamic pricing system used. Section III shows the different scenarios used for load shaping. Results and the analysis are presented in section IV. Finally, a conclusion is presented in section V.

II. Dynamic Pricing System Design

A. Load & Generation Profile

To be able to demonstrate the concept of the revenue breakdown, the daily load profile of a major city Amman-Jordan was assumed based on the work presented by [12]. A sample of the 24-hour load profile for a typical working and a typical non-working day in September is shown in Figure 1. Customers are assumed to be able to shift their load but would be using a fixed amount of energy during a given week.

A two-generator model is used in this simulation. The generation cost for each generator follows a quadratic model as shown in Equation 1 where C is the total cost of generation for one generation, and α, β, and γ are constants. P is the amount of power generated in a specific generator [1]. The total cost of the system is the sum of the generation costs of the two generators.

$$C = \alpha P^2 + \beta P + \gamma \tag{1}$$

The generation will be assumed to have an upper and lower limit. This is very typical in a real-life scenario. As generators have a maximum generation output as well as a minimum output power. These limits are noted as PUpper and PLower, and will be assumed as 50MW and 20MW, respectively. These values are consistent with the load profile of the city selected for the simulation. Note that for low demand, only one of the generators will be used. For higher demand, both generators will be used, and the power generated will be split equally between them.

B. Intelligent System Design

As mentioned earlier, the simulations in this work are based on the system outlined in [1], [2] and shown in Figure 2. The system relies on statistical modeling for the population of customers in terms of their awareness and flexibility to shift their load. Awareness refers to the customers' understanding of real-time pricing schemes, and how this can be effectively used to their advantage in terms of shifting their load to reduce their overall electric bill. A higher portion of the population, at this early stage of dynamic pricing schemes, are expected to be less aware of the implications of dynamic pricing, and as such, the probability that customers are 'aware' is expected to follow a weibull probability distribution, with the probability skewed towards lower awareness. Flexibility, on the other hand, refers to the customers' ability to actually shift their load to times of the day where the price is lower. This can be related to the customers' general lifestyle, and as such it is expected to follow a 'normal' distribution. Both Flexibility and Awareness concepts are explained in [2].

The system has access to the generation capacity limit as well as the expected demand based on the historical data. Based on this information, the system utilizes a fuzzy logic engine within the Customer Response Prediction Model (CRPM) to predict whether each individual customer will be shifting his/her load or not. Thus, it will be able to figure out if it will be able to meet the desired load target or not.

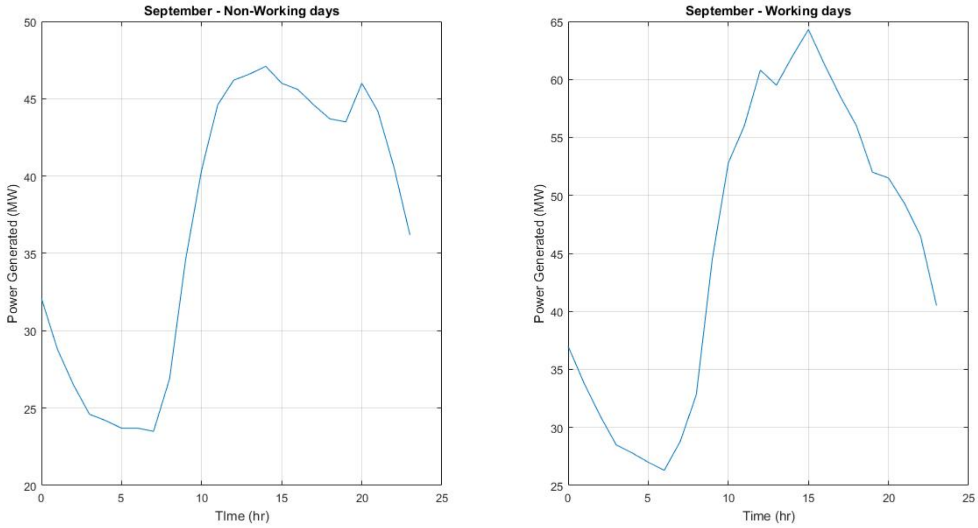

Fig. 1. Sample from the load profile of the city of Amman, for a typical working and a typical non-working day in September

If not, it would increase the incentive amount and repeat the simulation. The system assumes a cap of $\pm 25\%$ on the amount of the incentive. Based on the aforementioned mechanism the system is able to decide the optimal pricing point for the next day.

III. Test Scenarios

As part of the load shaping strategy, the dynamic pricing scheme can be used in two ways to shape the load profile: Clipping and Percentage Reduction.

Clipping, shown in Figure 3, is the technique where the dynamic pricing system attempts to keep the load within the limits of $P_{Eff_{Max}}$ and $P_{Eff_{Min}}$, this is achieved by increasing the prices when the load is expected to exceed the upper limit, thus discouraging consumers from consuming power. In addition, by introducing incentives when the load is expected to dip below the lower limit.

Meanwhile, in the percentage scheme, shown in Figure 4, the load is shaped by a certain percentage across the board. When the load is above the average load it is reduced by a predefined percentage. The farther the load from the average, the higher the amount of reduction in absolute terms. When the load consumed is below the average, the load is increased by that exact predefined percentage.

IV. Results and Analysis

A. Clipping: Controlling the Lower Limit

In this case, the upper limit is fixed at $46MW$, while the lower limit is varied from $(20-35)MW$. Figure 5 shows the breakdown of the profit generated for a population of Medium Flexibility and Medium Awareness. The figure shows whether the profit is due to saving in the generation cost (the blue column) or due to the additional charges paid by customers due to dynamic pricing (DP) (the red column). In cases where the profit due to DP is negative, this means that the utility company has in fact lost money in a form of incentives to customers to shift their load. It is clear from the figure that with inflexible customers the utility company ends up with a net loss as the saving in the generation are eclipsed by the incentives to shift the load.

For populations with high flexibility and high awareness levels, the results are shown in Figure 6. Initially, the utility company is losing money as the customers are very flexible and able to shift their loads and take advantage of the incentive. However, as the clipping is pushed towards higher values, the utility company starts making money from the DP scheme.

B. Clipping: Controlling the Upper Limit

In this case, the upper limit is decreased gradually from $(50-35)MW$. Again, results are presented for the M-M population in Figure 7. Here it can be seen that a major portion of the profit is due to profit from DP, and only when the clipping limit is set to $40MW$ the utility company starts making money from generation saving. This is because the second generator in the model kicks in at 40MW. It can be seen that a significant portion of the profit is actually due to profit from DP as customers are not able to shift their loads fully.

The picture changes for H-H population, shown in Figure 8. Here it can be seen that since customers are able to shift their load, the profit is due to the saving in the generation cost. Even when there is a loss due to DP, the utility company still ends up with a high profit due to the savings in generation cost.

C. Percentage Reduction

Here in this scenario, the attempt is to reduce the load deviation from the average by a varying percentage. This percentage is gradually varied from $(5\% - 100\%)$. Figure 9

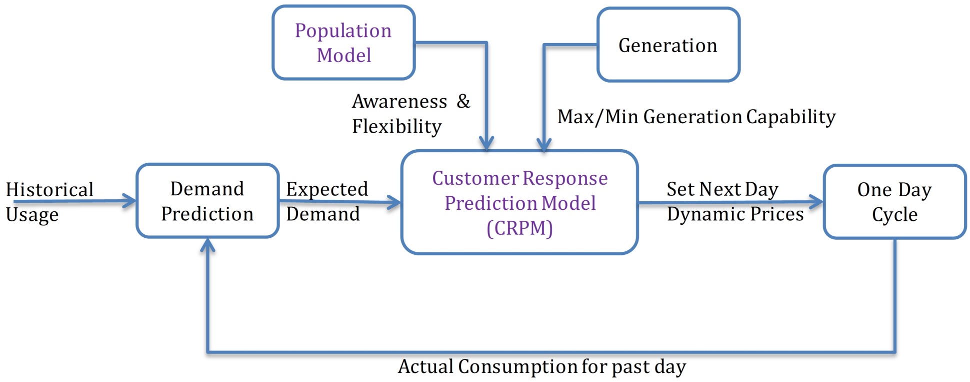

Fig. 2. Modules of the Intelligent Dynamic Pricing System [2]

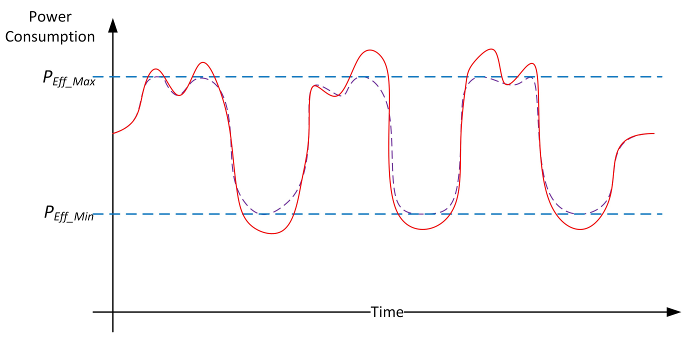

Fig. 3. Clipping Pricing Scheme [1]

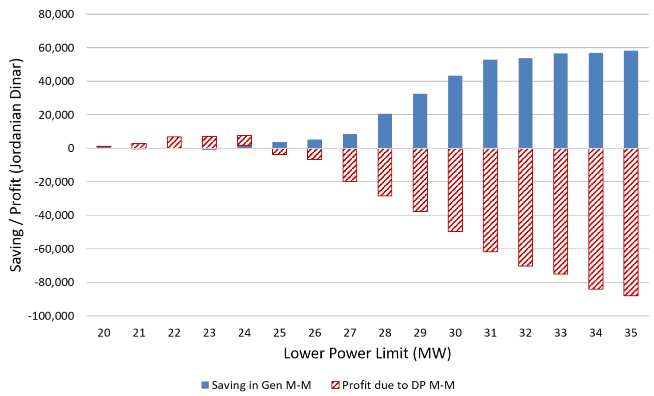

Fig. 5. Profit Breakdown for Clipping of Lower Limit for M-M Population

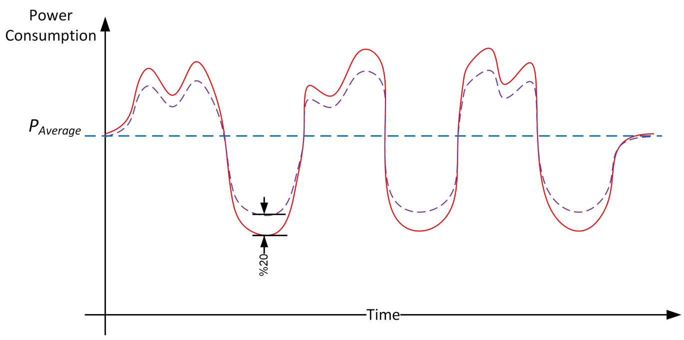

Fig. 4. Percentage Reduction Pricing Scheme [1]

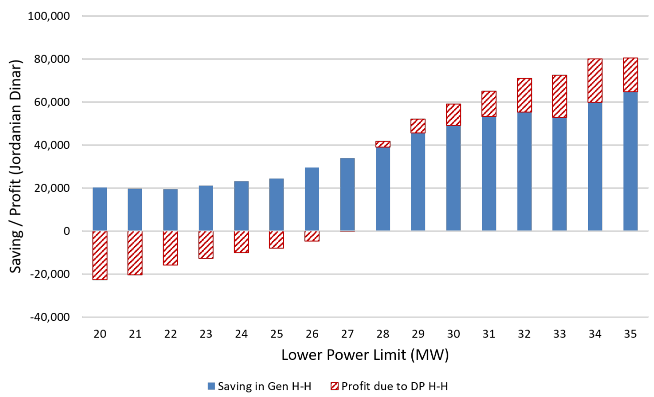

Fig. 6. Profit Breakdown for Clipping of Lower Limit for H-H Population

shows the profit breakdown for the M-M population. It can be seen that profits increase gradually as the demand curve is flattened. Also, it is obvious that both the reduction in generation costs and the profit due to DP are both contributing to the gradual increase in the profit.

Meanwhile, for the H-H population, shown in Figure 10, it is clear that the bulk of the profit is due to the savings in the generation cost. And that only a tiny fraction of the profit is due to the DP scheme. This is expected as people are switching their loads easily and not subjected to any additional premiums.

V. Conclusion

In this paper, two types of dynamic pricing schemes are compared in terms of the amount of added profit they generate to the utility companies. Profits can be due to either the reduction in the generation cost achieved from a more flattened demand curve, or it could be due to the increased income from the higher premiums in high demand times. These

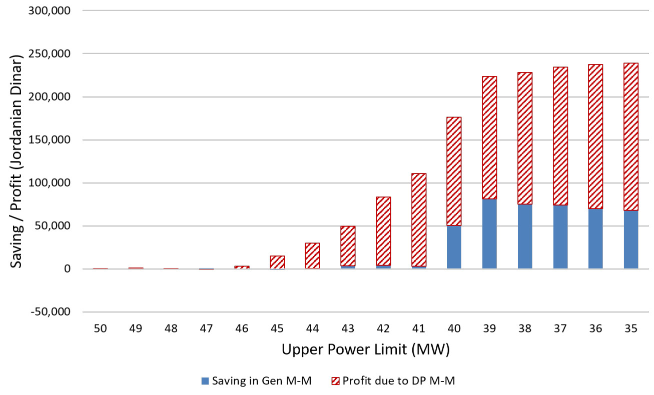

Fig. 7. Profit Breakdown for Clipping of Upper Limit for M-M Population

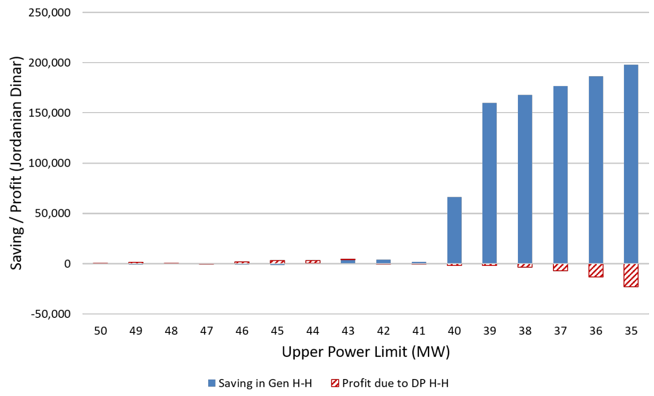

Fig. 8. Profit Breakdown for Clipping of Upper Limit for H-H Population

profits are also dependent on the levels of flexibility and awareness among the customer population. Results show that for populations with higher flexibility and awareness levels, the profits due to the reduced cost of generation are generally higher; while for medium flexibility and awareness levels, the higher profits come from the higher income from electricity premiums, as the population is more resistant to load shifting strategies. Future work will include other pricing techniques,

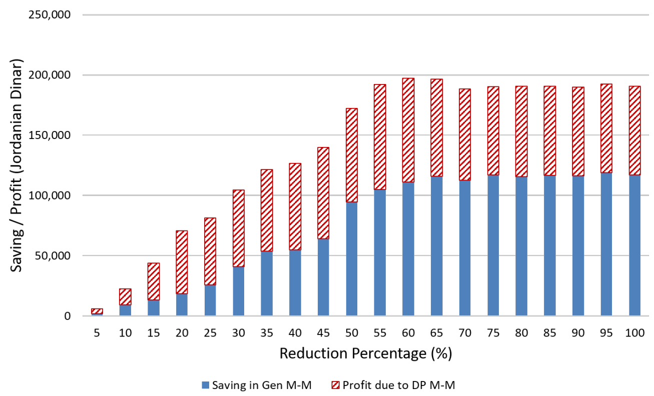

Fig. 9. Profit Breakdown for Percentage Reduction for M-M Population

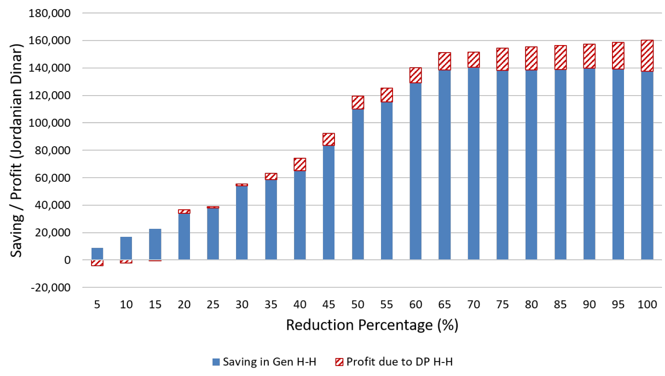

Fig. 10. Profit Breakdown for Percentage Reduction for H-H Population

as well as better modeling of the customer behavior in dynamic pricing environments.

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