Sepia : A Self-Organizing Electricity Pricing System

Deva P. Seetharam, Tanuja Ganu and Jayanta Basak

***Abstract*—The demand for electrical power is not constant. There are certain times of the day where the demand levels are much higher than the rest of the day. The demand can often exceed the generation capacity and when that happens, the utility companies can either shed loads or buy additional electrical energy from wholesale electricity markets to close the gap between demand and supply. These markets clear energy at spot prices that fluctuate widely and can be much higher when the demand is high than when the demand is low. When the market rate for electricity rises above the approved retail rate, utilities are caught in the middle, which can be financially disastrous for them.**

As such, utility companies, to protect themselves from widely fluctuating costs and to reduce peak demands, are introducing Advanced Metering Infrastructure (AMI) and considering various dynamic pricing mechanisms such as Time Of Use (TOU) and Critical Peak Pricing (CPP). However, in these mechanisms, there can be both a significant delay in information reaching consumers and gaps in consumption data. These delays and gaps can undercut the premise of how smart meter technologies will empower consumers to make decisions about their electricity use based on real-time prices. Moreover, these pricing schemes are centralized, in the sense that, meters at customer premises connect to the utility systems to obtain the current price. Such a centralized systems are inefficient because they require substantial communication and computation resources.

To address these shortcomings, we propose Sepia, a self-organizing real-time electricity-pricing scheme, that computes the price of a kilowatt-hour of electricity as a function of consumption history, grid load and the type (hospital/commercial/industrial etc.) of the customer. In this paper, we describe the details of this pricing scheme and demonstrate, using a simulator, how this scheme could potentially alter the consumption patterns.

***Index Terms*—Intelligent services, Energy Prices, Self-organizing prices, Electricity Prices, Frequency, Consumption History, Current Load, Customer Segment.**

I. Introduction

THE demand for electrical power is not constant. There are certain times of the day where the demand levels are much higher than the rest of the day [1]. For instance, residential demand is much higher in the morning (around 7 AM), when a large number of people leave for work and in the evening (around 7 pm), when those workers return home. (Obviously, these demand patterns depend on the consumer segments and market areas.)

When the peak demand exceeds the available generation capacity, the utility companies either resort to shedding loads or to buying additional power from other utilities through wholesale electricity markets such as the Indian Energy Exchange [2] and the New York Independent System Operator [3], etc.[1] These markets clear energy at spot prices using mechanisms such as Availability Based Tariff (ABT) [4] and Locational Based Marginal Pricing (LBMP). These spot prices fluctuate widely and can be much higher when the demand is high than when the demand is low. For example, based on the current grid frequency (indicates the current grid load), the ABT prices can vary between Rs. 0 to Rs. 5.70 per KWh of energy [4]. The utilities can't pass on these rate fluctuations to customers because non-commercial customers are protected by flat-rate electric tariffs. When the market rate for electricity rises above the approved retail rate, utilities are caught in the middle, which can be financially disastrous [1].

To alleviate this peak demand problem, utility companies are trying to shift the loads from peak-load periods to off-peak periods so that the peak loads of users will be distributed over the day instead of concurring at peak hours. Such an approach is possible because some loads (such as washing machines, electric vehicle charging, dishwashers etc) can be deferred and some other loads (such as air conditioner, refrigerator, etc) can be reduced. Such load management can be achieved through indirect load control (manual procedures) or direct load control (automatic procedures with the help of network-enabled smart appliances).

Utility companies have started introducing smart meters[2] and exploring various dynamic pricing mechanisms to reduce peak loads and to even out loads during the day. Some of the pricing mechanisms being considered are time of use (TOU), critical peak pricing (CPP), real-time pricing (RTP) and peak load reduction credits (PLRC). However, these schemes suffer from certain shortcomings:

- In TOU schemes, the energy prices are static and can change only very infrequently.
- Many of the proposed RTP schemes require the meters (at customer premises) to connect to the utility systems to obtain the current price. Such a centralized approach is inefficient, as it requires substantial communication and computation resources.

To address these issues, we propose *Sepia*, a decentralized electricity-pricing scheme, that dynamically adjusts the rates according to the current load on the grid and the past consumption history.

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[1]It is important to note that since electrical energy cannot be stored efficiently for long periods, utilities can't use energy generated during off-peak periods to meet peak demands.

[2]A smart meter is an advanced meter (usually an electrical meter) that records consumption in intervals of an hour or less and communicates that information at least daily via some communications network back to the utility for monitoring and billing purposes (telemetering). Smart meters enable two-way communication between the meter and the central system [5].

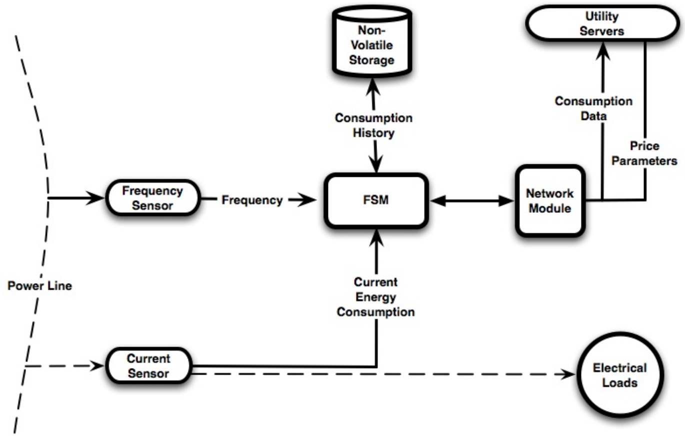


Fig. 1: System Block Diagram

II. Approach And System Overview

Sepia is based on Frequency Sensing Meters (FSM). An FSM is nothing more than a smart meter equipped with a simple inexpensive frequency sensing circuitry. The frequency sensor is used to measure the grid frequency, which is inversely proportional to the current load on the grid. The Sepia scheme works as follows:

- Once every sampling period (say 10 or 15 minutes), the FSM measures the average frequency of the grid (GF) during that sampling period.
- The FSM uses the sensed frequency, GF, to map it to the price, on the Frequency-vs-KWH-rate curve specified by the utility company. This curve can be specific to customer segments as illustrated in Fig. 2; and can vary according to seasons. The current rate, CR, can be defined as a function with a certain slope δ, a minimum price (corresponding to maximum frequency) and a maximum price (corresponding to minimum frequency).

$$CR = f(GF) \tag{1}$$

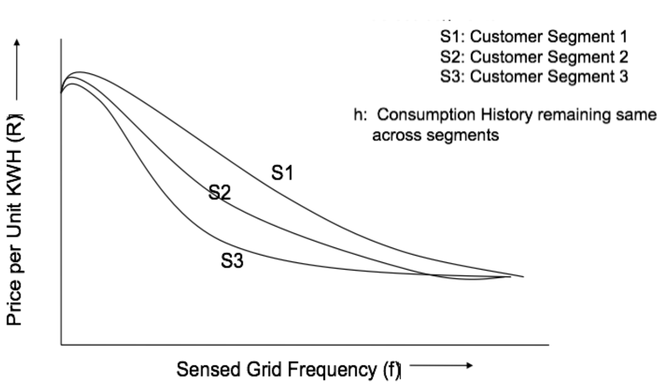


Fig. 2: Customer-segment Specific Electricity Rates

- The current rate (CR) can be further refined by a Penalty Factor (PF) as shown in the equation below.

$$CR = CR \times (1 + PF) \tag{2}$$

The penalty factor enables the system to further amplify the current rate based on customer-specific parameters such as income class, past consumption history and type of usage. These parameters are just listed for illustration purposes. System can be configured to use a completely different set of parameters.
- The different components of the penalty factor can be emphasized or deemphasized or even eliminated (if the corresponding weight is zero) using component-specific weights. For instance, if usage U (residential/commercial etc.), income class I (low/medium/high) and past consumption history H are the Penalty Factors, they can be modulated using different weights (like w_u, w_i and w_h) as given in the equation (3).

$$PF = w_u \times f(U) + w_i \times f(I) + w_h \times f(H) \tag{3}$$

- It is worth noting that the Penalty Factor, using weights, can be adjusted so that the CR specified in equation (2) can be multiplied by a real-number factor that falls between 1.0 and 2.0.
- Customer-specific information such as weights, past consumption history, usage and income class are retrieved from the non-volatile storage to compute penalty factor.
- Electricity consumed for the current measurement period is obtained integrating the instant power consumed by that particular customer during that measurement period.
- Now, the current energy charges can be computed as product of the current rate and the amount of energy consumed during the current sampling period.
- FSM periodically uploads electricity charges to and downloads pricing parameters from the utility's pricing servers.
- The FSM also stores various factors such as frequency, current consumption data and consumption history in the non-volatile storage for future computations and for auditing purposes.

The benefits of Sepia are:

- If majority of the customers are price sensitive, this scheme can reduce the energy consumption by adjusting the unit rates. It is important to note that the scheme can also encourage consumption by reducing rates during off-peak periods.
- It can support customer segment specific unit rates.
- Since it includes consumption history (assigned weights decreasing with time) in determining the electricity prices, customers who were consuming heavily will be charged more than the ones who were not. This probably will lead to fairer rates than otherwise.
- By setting the function parameters to the appropriate values, any factor (history or current frequency) can be emphasized or de-emphasized.
- Scheme is resilient to network or computation failures as it functions in a decentralized fashion.

III. Related Work

Several differential pricing schemes for electricity have been proposed [7]:

A. Time of Use Pricing (TOU)

In TOU schemes, electricity prices are set for a specific time period on an advance or forward basis, typically not changing more often than twice a year, based on the utility's cost of generating and/or purchasing such electricity at the wholesale level for the benefit of the consumer. Prices paid for energy consumed during these periods shall be pre-established and known to consumers in advance of such consumption, allowing them to vary their demand and usage in response to such prices and manage their energy costs by shifting usage to a lower cost period or reducing their consumption overall.

The scheme is simple and fairly easy to implement. In fact, it doesn't even require the smart meter infrastructure. However, since the scheme is not that "dynamic", the TOU pricing variations will reflect very little of the true variations in the wholesale energy markets.

B. Critical Peak Pricing (CPP)

In this scheme, time-of-use prices are in effect except for certain peak load times, when prices may reflect the costs of generating and/or purchasing electricity at the wholesale level and as a result the prices can be unusually high for a limited number of hours.

CPP scheme is the natural evolution of demand charges when more sophisticated metering is available. Charges increase at critical system peaks rather than at the individual customer's demand peak, which is much more consistent with the true costs of consumption. CPP still has two economic weaknesses, though they may actually be strengths in terms of customer acceptance. First, the prices are limited and levels are preset for the critical peak periods, therefore they can't be calibrated to move with the actual prices in the wholesale market. Second, the number of critical peak hours that can be called in a year is limited [7].

C. Real Time Pricing (RTP)

In this scheme, electricity prices are set for a specific time period on an advanced or forward basis, reflecting the utility's cost of generating and/or purchasing electricity at the wholesale level, and may change as often as hourly.

RTP does not mean that customers must buy all of their power at the real-time price. Purchasing some power through a long-term contract would allow customers to stabilize their overall bill while still facing the real-time price for incremental consumption.

Unsurprisingly, RTP can closely follow the variations in wholesale energy prices. However, implementing RTP has a few issues [7]:

- Customer pricing risk - many customers balk at RTP because they fear that they could find themselves paying astronomical prices for their consumption during any given hour.
- Distributional impacts - one of the major concerns with RTP is that it is not clear who will be the winners and who will be the losers in adopting such a time-varying price scheme.

In our scheme, customer risk is mitigated by customer-segment-specific rate curves that impose a limit on maximum rate per unit of energy. Limiting the prices to pre-defined maximum and minimum values allows the users to estimate the range in advance and plan their consumption. The distributional impacts of Sepia are still unknown. We will try to understand that in our future research. The idea of using real time pricing as an economic load shedding policy to assist the direct control by the electric utility is not new. Berger and Schweppe [8], in 1989, presented such an approach. However, their scheme doesn't support customer-segment specific pricing or incorporation of consumption history in rate calculations. We believe these two aspects are important in implementing a fair pricing scheme.

IV. ASSESSMENT AND EVALUATION

A. Simulation Setup

We demonstrate the functioning of Sepia using a discrete event simulator that models the users' price sensitivity, the proposed dynamic electricity-pricing scheme *sepia* and users' response to varying electricity prices.

At every time step, the simulator computes the following quantities:

a) Time of Use Probability: Time of Use probability determines the chances of a customer using electricity at a specific time of the day. We are using the residential usage pattern as the reference for computing this probability. As explained above, residential usage probability is a bimodal distribution with one peak occurring in the morning and the other in the evening. The equation for calculating this ToU probability is given below.

$$TOUProbability = \frac{e^{-(t-T_1)^2}}{2\sigma_1^2} + \frac{e^{-(t-T_2)^2}}{2\sigma_2^2} \tag{4}$$

where, t is current time, T_1 and T_2 are the times for the first and second peaks respectively, and σ_1 and σ_2 are the widths of first and second modes. In the simulation runs, we assumed that the two consumption peaks occur at 6 AM and 6 PM.

b) Current Unit Rate: We are using a sample of population of 1000 consumers that belong to different consumer segments, comprising of a combination of three different income classes - low, medium and high - and three different electricity usage types - residential, commercial and transportation. We start with a rate of 10 cents per unit of electricity. The current rate gets modulated by a Penalty Factor (PF) that comprises income class, usage type and consumption history. These three factors are assigned a weight of 0.4, 0.2 and 0.6 respectively. In other words, consumption history dominates the penalty factor and the income class has the least influence. History is based on the consumption for a consecutive last 'n' time periods (where 'n' is given by History window). A history consumption threshold is considered above which the consumer provides a penalty.

c) Consumption Probability: Consumption probability determines the probability with which a particular customer will use electricity given the current rate for a unit of electricity. We are using an illustrative price sensitivity curve, shown in Fig. 3, as the basis for computing this quantity. The

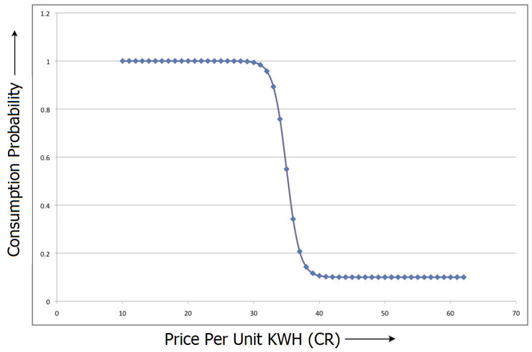


Fig. 3: An Exemplary Price Sensitivity Curve

consumption probability (CP) is computed as follows:

$$CP = \frac{a + e^{(m(k-CR))}}{1 + e^{(m(k-CR))}} \tag{5}$$

where, a is the minimum consumption probability, k is the price at which the user's consumption falls and m is the rate of consumption with rising prices. If the current unit rate is high, the probability that a customer will consume electricity is low and vice-versa. Therefore consumption probability is inversely proportional to the current unit rate and is a good indicator of customer's price sensitivity.
Each consumer has three types of loads: a) Base load: loads such as lighting that are essential cannot be deferred or reduced. b) Deferrable load: loads such as washing machines that may not be time sensitive and can be deferred to a convenient time. c) Reducible load: loads such as AC that can be reduced to save energy. If the consumption probability is low, a consumer is expected to run only the base load, postpone a portion of deferrable loads and reduce a proportion of reducible loads. The portions of loads that are reduced and deferred are determined using a random number generator.

d) Current Grid Frequency: As explained above, the load on the grid impacts the current grid frequency. Total load is computed by summing up the electricity consumed by every single member of the population and then grid frequency can be computed using the equation below.

$$f_\delta = \frac{P_g - P_c}{P_g} \times \frac{f_o}{f_r} \tag{6}$$

where f_δ is the change in the frequency, P_g and P_c are the generated and consumed powers respectively, f_o is the operating frequency of the grid (50 Hz or 60 Hz depending upon the geography) and f_r is a constant frequency response (considered as 15 in the simulations).

B. Evaluation

We ran the simulation using the penalty factors for different consumer segments as discussed in Section IV-A(b).

The simulator considers varying population size with different segments of consumers in terms of income class and usage type. For our results we have considered a population size of 1000 consumers, which is skewed for, middle-income population.

The base (around 50-100watts), maximum typical power requirements (2KW) and total generation capability also assume real world scenarios [9] but can be set to different values based on regions. History window shows the number of recently used intervals considered for PF. History window threshold determines the number of values that are higher than threshold for providing a penalty to the consumers. Threshold for considering high consumption is dynamic and is set to 400 units for typical power requirements of 100-5000 units. The payoff for different consumer segments is controllable. The simulator is run for total duration of 5700 mins (but we have presented results for 1440 mins for purpose of brevity and clarity).

We evaluate the following scenarios:

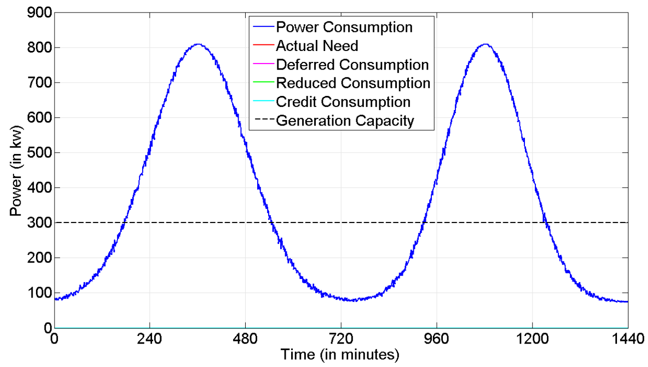
(a) Limits in the reduction of the peak loads for different consumption probabilities.

(b) Evaluation of *Sepia* pricing scheme using a mix of customer segments.

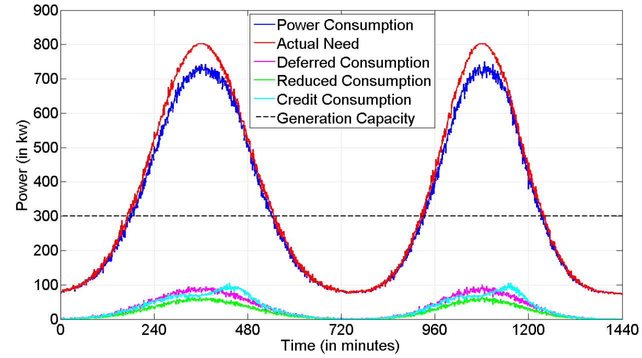
1) Limits of peak reduction: We study the limits of peak reduction that can be achieved by introducing dynamic pricing. In our experiments this is achieved by controlling the consumption probability. We plot the consumption graph for different values of the consumption probability.

Fig. 4 plots the different power usage patterns for different values of the consumption probability. The TOU probability follows the pattern shown in Fig. 5 with 2 peaks in the day showing high usage patterns. The graphs clearly indicate that by controlling the consumption probability (by different parameters) the peak load (which exceeds the generation capacity) can be reduced significantly. It can be clearly seen that as the consumption probability reduces, the deferred power and the reduced power increases, leading to lower power usages during the peak hours.

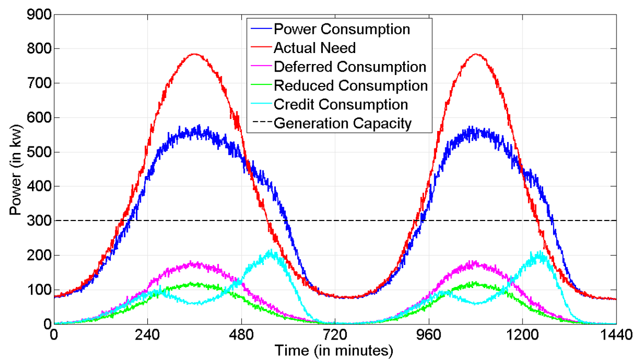
There are two important observations from these graphs: (I) Fig. 4(a) presents the scenario when the consumption probability is 1 i.e. when the power usage is uncontrolled. In this scenario, the power consumption exactly matches the actual power need and no deferred, reduced or credit loads (rescheduling of deferred load during off-peak time) are observed. In Fig. 4(b) and (c), as the consumption probability decreases, indicating more price sensitivity, it results in a significant decrease in the peak power consumption. In this scenario, some proportion of the actual power requirement is deferred or reduced during the peak time. The deferred load is completely rescheduled (as credit consumption) during non-peak times using the greedy approach. When the consumption probability decreases further to 0.4, as shown in Fig. 4(d), it results in further reduction in the peak power consumption. But, since the consumption probability is low through out the day, some proportion of the deferred load remains unfulfilled. (II) We expect that the deferred load to be scheduled during non-peak times as opposed to the simulation results where the peak load is scheduled in a greedy manner as soon as



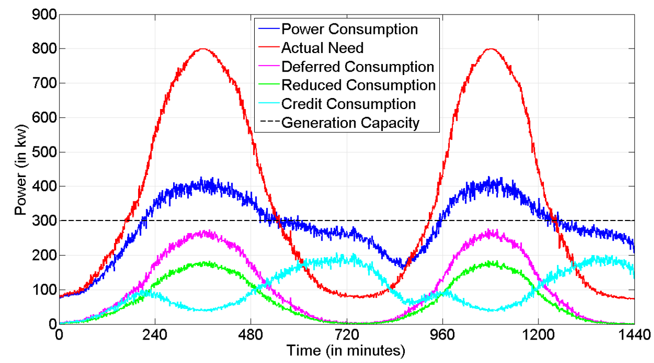
(a) Consumption Probability 1 : No price sensitivity



(b) Consumption probability 0.8 : Low price sensitivity



(c) Consumption probability 0.6 : Medium price sensitivity



(d) Consumption probability 0.4 : High price sensitivity

Fig. 4: Load variations as a function of consumption probability

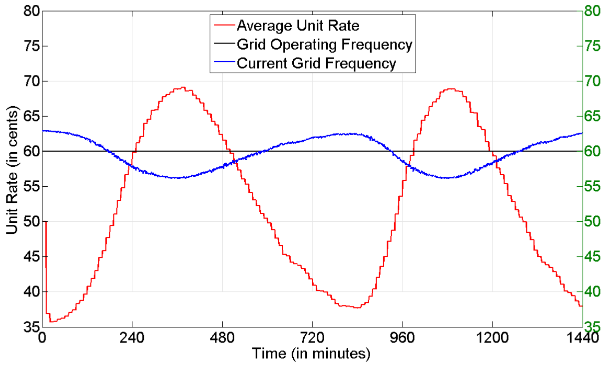
the next slot is available. The deferred loads are clustered immediately after the peak loads. It should be noted that the simulation chooses to schedule the load over the next available slot when the extra power is available thereby leading to minimal diffusion of power usage over time when the consumption probability is low. In Fig. 4(b) for consumption probability of 0.8 (low price sensitivity), the deferred load at time 360 minutes is scheduled between 420- 480 minutes approximately. This is due to the fact that individual power consumption is upper-bounded at 1.5 KW in our experiments and therefore when the consumption falls below this, the deferred load is scheduled. This approach is greedy and therefore significant benefits are obtained only when the consumption is tightly controlled (probability is 0.6 or 0.4, where the loads are deferred repeatedly) or the consumption probability varies during a day as shown in Fig. 5(c). This leads to an important aspect that scheduling algorithms (which we have not simulated in our work) should be designed to take input from the grid about the availability of the power and intelligently schedule the load rather than taking a greedy approach.

2) Evaluation of Sepia pricing scheme: We study *sepia* pricing scheme by considering a mix of customer segments Fig. 5(a) presents the change in average unit rate with the change in current grid frequency. Note that the unit rate is computed at 10-minute time interval based on the average grid frequency during that time period and the consumer specific penalty factors. Hence, it shows a squared form. The average unit rate is high when the grid frequency is low (i.e. during peak times) and vice versa. Fig. 5(b) shows the time of use probability and the average consumption probability for the given mix of customer segments. As the average unit rate increases, the average consumption probability decreases and vice versa. Fig. 5(c) shows the effect of sepia pricing scheme on the actual power consumption. It is observed that a significant proportion of actual electricity requirement is deferred or reduced during peak time, when the unit rates are high and the consumption probability is low, thereby resulting in a significant reduction in peak power consumption.

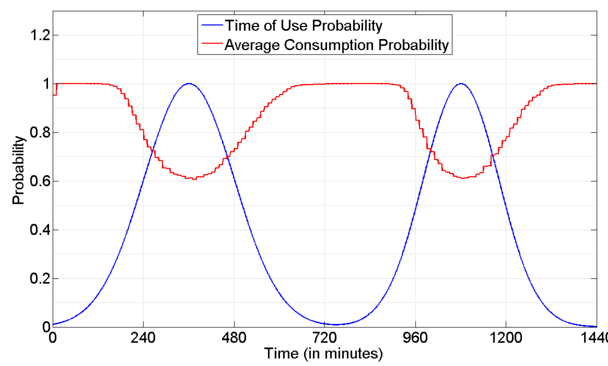
Metric	Sepia	Fixed price
PAR	**1.7931** $\pm$ 0.001	2.2573 $\pm$ 0.001
% Over-utilization	**27.33** $\pm$ 1.12	39.63 $\pm$ 2.31
% Under-utilization	**18.05** $\pm$ 0.76	24.11 $\pm$ 1.24

TABLE I: Summary of simulations for different pricing schemes based on three metrics: peak-to-average ratio (PAR), %Over-utilization and %Under-utilization.

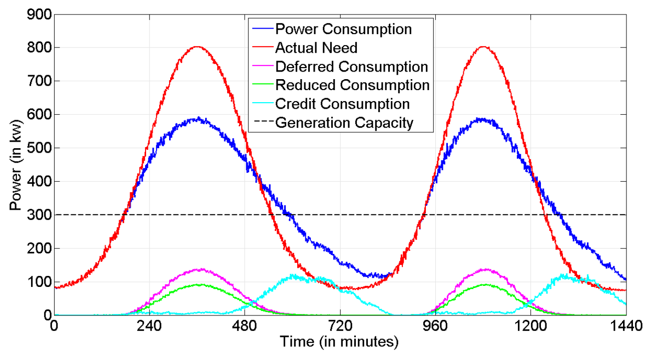
Table I presents the summary of simulations based on three metrics: peak-to-average ratio (PAR) [11], %Over-utilization (proportion of the consumption above the generation capacity) and %Under-utilization (proportion of the consumption below the generation capacity). It is observed that sepia scheme helps to reduce peak-to-average ratio, and decreases %over-utilization and %under-utilization as compared to the fixed pricing scheme.



(a) Variation in Unit Rate as a function of Grid Frequency



(b) Time of Use Probability and Average Consumption Probability for the simulated population



(c) Peak Load Reduction

Fig. 5: Evaluation of *Sepia* dynamic pricing scheme using a mix of different customer segments

V. Discussions and Future Work

In this work, we proposed a dynamic energy pricing that could sensitize customers to current load on the grid. In fact, Newell and Faruqui [10] argue that the wholesale market benefits that could be expected if all retail customers were provided dynamic price signals, similar to those price signals now available to participants in New York's wholesale electricity markets. The authors predict the dynamic pricing, if adopted by the New York State, could reduce cost and demand while improving social welfare.

As discussed in the evaluation section, the pricing scheme can reduce consumption. However, if this pricing system were to be deployed widely, it must incorporate provisions for not charging the customers when the frequency falls due to power system faults. Further, if the utilities artificially impose frequency regulations in order to maintain the grid frequency within a small fixed range, the voltage signal can be used (by doing careful analysis) instead of grid frequency for calculating unit rate. Though sepia protects the privacy of consumer's electricity consumption data and other parameters by using a one-way unit rate calculation function, the meters must be made tamper proof so that the meters from the customer segments with lower rates are not moved to customers with higher rates. For instances, it must be ensured the meters installed in hospitals are not moved to commercial establishments. The scheme also requires learning capabilities so that it can adjust the pricing parameters to adapt itself well to new electricity markets such that the electricity demand and supply are matched without overburdening the customers or the electricity retailers.

Acknowledgment

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