Economics of Customer's Decisions in Smart Grid

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Abstract

In this paper, we study the problem of allowing customers to use their storage energy, grid energy, as well as privately owned renewable sources of energy. The customer has three options — grid, storage, and self-generated energy, to fulfill the energy requirements. The grid decides real-time price to maximize its revenue, while ensuring customers' participation depending on three factors — *demand*, *supply*, and *time of use*. On the other hand, a customer needs to choose strategies on his/her required energy and associated cost, depending on the storage and self-generated energy, to maximize the pay-off. We use Markov Decision Process (MDP) to design this decision making policy of the customer. In such a MDP-based decision model, a cost-effective energy management process is established, and, thus, utility of the customers is maximized. Simulation results show that using the proposed approach, the customers decide the strategies to optimize a trade-off between energy exchange and associated cost. Thus, the utility for customer is increased approximately 60% with the presence of grid, storage, and self-generated energy sources than that of using only grid and storage energy.

Index Terms

Self-generation, Storage, Pay-off, Energy Management, MDP, Smart Grid, Networks

I. Introduction

Smart grid is envisioned as a combination of underlay electricity networks with overlay communication networks for providing reliable, and efficient energy supply to the end-users [1]. Thus, it requires an extensive use of modern information and communication technologies, together with sensors, smart meters, and power electronics from the supply side to demand side [2]. On the other hand, distributed generation (DG) units are expected to play an important role for reliable energy supply to the customers during on-peak hours [3]. In the existing power system, customers are serviced by a central electric grid that delivers power to the end-users over low voltage distribution networks. In the presence of energy storage devices, as well as self-generation, it is desirable to allow the customers to use the stored energy and self-generated energy, so as to relieve the demand from the main grid.

A. Motivation

A micro-grid distributes electricity to the end-users from transmission electricity networks with grid energy, stored energy, and some renewable energy sources (e.g. solar and wind) [4]. During on-peak hours, the micro-grid uses stored energy, fuel cells, and small-scale combined heat and power (CHP) with the main grid energy during on-peak hours. However, the customers may have to wait to get energy when the demand is very high or total energy demand is higher than the total supply. In such a condition, the existence of stored and self-generated energy at the customers' end will be cost-effective and reliable for energy supply during on-peak hours. Consequently, customers need to take optimal decisions to get advantages of stored and self-generated energy in order to maximize their utility. Therefore, we consider a utility provider, which distributes energy from the main grid. A customer consumes energy from this utility provider. Let at any instant time, t, a customer's required energy be x_i, $i \in \mathcal{N}$, and let the real-time price given by the grid be p_t. Additionally, the customer has stored energy, s_i, and self-generated energy (g_i). In such a condition, a decision needs to be taken by the customer, i.e., from where the customer should consume energy, so as to fulfill the requirement of energy with optimal cost.

B. Contribution

In this paper, we introduce a decision model that can help customers to make strategies for proper utilization of storage and self-generated energy with the grid energy. We use MDP-based decision approach to make strategies for the customers, so as to fulfill the energy requirements in order to maximize the pay-off. The customer takes decisions depending on his/her satisfactory price, and again sends the information to the grid according to the levels of stored energy, self-generated energy, and discount factor (γ) received from the grid. We show that the customer can maximize his/her pay-off with the implementation of self-generated energy sources. In summary, our contributions in this paper is as follows.

- We present a decision model for real-time energy consumption of the customers in presence of grid, storage, and self-generated energy.
- Markov decision process (MDP) is used to evaluate the optimal strategy of the customers for cost-effective energy consumption.
- We also present an algorithm for grid to determine real-time price of energy while taking customers' participation. Additionally, algorithm for customers is also presented for cost-effective energy consumption.

The rest of the paper is organized as follows. We briefly present the related literature in Section II. Section III describes the system model with energy consumption profile of the customers. In Section IV, we formulate the optimal strategy using MDP and present the corresponding algorithms. In Section V, the results and performance are discussed. Finally, we conclude the paper with few research directions in Section VI.

II. Related Works

In the recent years, several works have been done on smart grid implementation [5]–[20]. Some of the existing literature are discussed in this Section. In [6], the authors proposed that with the implementation of wind generation and storage devices, efficient and economic operation of electric power distribution system can be improved. In such a scenario, they proposed that in a certain area, there are some storage devices and some wind generation, and these are controllable by micro-grid. According to the demand, the micro-grid decides whether or not to use storage and wind generation. The rate variation of wind power is also controlled to have smooth energy supply to the customers.

In [7], the authors proposed a distributed load management scheme, in which customers know their energy usage, and use energy according to a dynamic pricing mechanism. The dynamic pricing strategy is modeled as network congestion game. The Nash equilibrium is also presented in order to have the optimal solution. However, in this case, if the customer requires more energy in a certain time, then he/she has to wait for some time until distributed generation can manage it. In [8], Bakker et al. proposed a reliable power supply in smart grid by introducing the concept of smart meters, distributed generation, storage, and demand side management. In such a demand side management scheme, three steps are evaluated for cost-effective energy supply. In first steps, users predicted energy generation and consumption for upcoming day. In second and final steps, grid optimize the total energy demand by the customers and a real-time control algorithm evaluates at what time appliances are to be switched on/off based on total demand, respectively. Load shifting and storage device management are proposed in [9]. The authors proposed that during peak-hour, heavy loads should be turned off and vice-versa. The control mechanism is compared with real storage devices to show the impact of the load shifting scheme in smart grid. However, in this case also, if the customer does not want any delay to get energy, he/she has to pay a high price for it.

On the other hand, Molderink et al. [10] proposed an approach for using the energy in the non-peak or on-peak hours by establishing a virtual power plant (VPP) for energy management with a detailed analysis of the three steps mechanism discussed in [8]. Additionally, they showed that renewable energy sources are useful to achieve cost-effective and environment-friendly (CO_2 reduction) energy supply to the end users. In [11], the authors proposed an algorithm to allow customers' strategies, based on their advanced knowledge of the market. The authors discussed about storage devices and benefits from storage implementation. In [12], the authors proposed a time-to-use-aware energy management scheme. In this scheme, a customer uses energy according to the time whether it is on-peak hour or non-peak hour. In such a scenario, the customer waits for a time-bound during on-peak hour (i.e., price is

TABLE I: List of Symbols

Symbol	Description
x_i	Required energy of customer i
s_i	Storage energy of customer i
g_i	Self-generated energy of customer i
$\mathcal{E}_i$	Requested energy from customer i
$\mathcal{E}_t$	Total supply to the grid
p_t	Real-time price decided by grid
p_{si}	Satisfactory price of the customer
c_t	Cost of supply per unit energy
c_{si}	Cost of storage energy per unit
γ	Discount factor
$\mathcal{C}_\phi$	Total cost to the customer
$\mathcal{U}_n^c$	Utility of the customer
$\mathcal{U}_g$	Utility of the grid

high) to minimize the energy cost. On the other hand, customer consumes the energy if the waiting time is beyond a threshold value.

In [13], game theory is discussed for addressing various problems in the areas of micro-grid systems, demand-side management, and communications in smart grid technology. The authors proposed that the future smart grid is envisioned to encompass a large number of micro-grid elements. Hence, whenever some micro-grids have an excess of power, while other micro-grids have a need for power, energy exchange takes place among them. Different energy management schemes are proposed in [14]. However, in smart grid, new opportunities for more improved residential energy management and bill reduction for both sides (grid and end-users) are studied without considering the impact of self-generated energy services at the customers' end.

III. System Model

Let us consider a power system consisting of a main grid, several substations, and micro-grids. All the substations are connected to the main grid. We assume that a utility provider distributes energy to the end users with the help of micro-grids in a certain area. A customer subscribes energy from the utility provider. The utility provider dynamically changes the price (p_t) according to the supply from all the energy sources and demand from the customers.

Figure 1 shows the schematic diagram of a smart grid, in which each customer has its own storage device and self-generation. There are customers, i and j, where $(i, j) \in \mathcal{N}$ and $i \neq j$, are connected to different micro-grids. Micro-grids are connected to different substations to exchange energy with the main grid. Customers consume energy from the main grid with the help of related micro-grids connected to them. The customers can also communicate

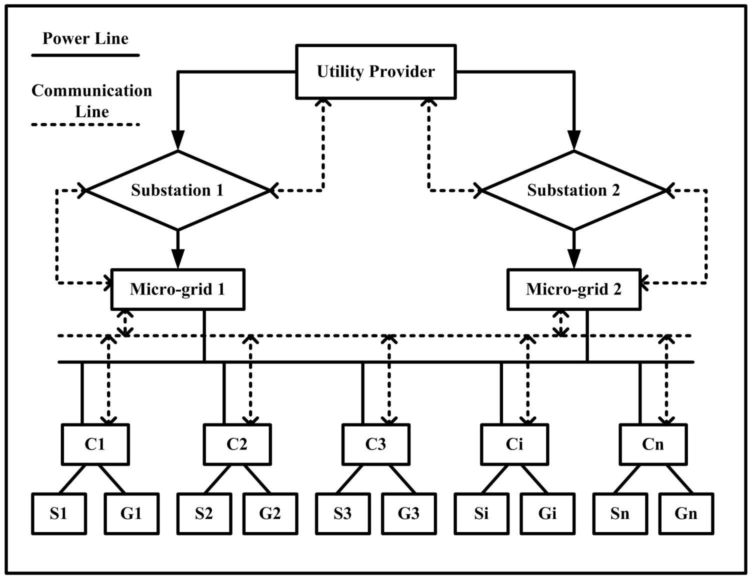

Fig. 1: A schematic view of Smart Grid

with the micro-grid according to demand and associated cost. By making strategies, they subscribe to energy from the main grid, storage, and self-generation sources.

A. Energy Consumption Profile

Each customer requests a certain amount of energy, x_i, $i \in \mathcal{N}$, from the grid to fulfill its requirement for the time interval, t. We assume that the customer has some amount of storage energy, s_i, with capacity, c_i, efficiency, ψ_i, and running cost, c_{si}. Also, the customer has self-generated energy, g_i, with some constraints (i.e., environmental condition, and time of use). The grid decides a dynamic price, p_t, per unit of energy in order to maximize its revenue while taking into account the customers' participation. Depending upon the price, p_t, the customer makes strategies over the storage profile, s_i, and the self-generated profile, g_i, so as to maximize the pay-off i.e.,

$$\text{Maximize} \mathcal{U}_c(x_i, s_i, g_i, p_t, c_{si})$$

subject to

$$x_i^{min} \leq x_n \leq x_i^{max}, \tag{1}$$

$$p_t \leq p_{si}, \tag{2}$$

$$x_i = s_i + g_i + \mathcal{E}_i, \tag{3}$$

where $i \in \mathcal{N}$. Equation (1) represents that required energy of a customer, i, has a minimum and maximum value as x_i^{min} and x_n^{max}, respectively. On the other hand, p_{si} is the satisfactory price of the customer depending on real-time price, p_t, decided by the grid as denoted in Equation (2). In Equation (3), total demand, x_i of the customer is fulfilled by its storage, self-generated and grid energy. In the optimization problem, all the energy demand parameters are greater than or equal to zero, i.e., s_i, g_i, and $\mathcal{E}_i$ are real and positive.

At the same time, demand from all customers must satisfy the total supply, i.e.,

$$\sum_i x_i \leq \mathcal{E}_t \qquad \text{where } i \in \mathcal{N} \tag{4}$$

Equation (4) shows that the total energy demand from all the customers should always be less than or equal to the total energy supply in order to have reliable energy supply to the end users.

In Figure 1, both the customer and the micro-grid interact with each other, and agree on the parameters (i.e., real-time price, p_t, and required energy, x_i) to successfully trading the energy exchange. Thus, the grid and the customer fulfill the objectives from both the sides.

B. Real-time Pricing model

The grid decides real-time price, p_t, depending on the received demand, x_i, from customer, i. Therefore, we use a linear pricing model as depicted in [21] as follows.

$$p_t = \alpha x_i^2 + \beta x_i + c \tag{5}$$

where x_i is the received demand from the customer i, and α, β, and c are the predefined constants. Consequently, Equation (5) denotes that p_t is directly proportional to the received demand from the customer, i.e., the real-time price is high with a high demand from the customer and vice-versa.

IV. MDP-Based Optimization Algorithm

A. MDP Process: State and Action Space

To study the interaction between the grid and the customer, we use MDP [22]–[26] to design the decision making process. Here, customer acts as Player 1, and grid acts as Player 2. Based on the demanded energy (x_n) from customer, Player 1 sends a request to the grid, i.e., Player 2. The Player 2 chooses some strategies to optimize its revenue. According to the Player 2's strategies, the Player 1 also chooses strategies to maximize the pay-off, and so on. Here, we choose such an environment as an MDP.

The decision strategy is defined as follows:

$$\mathcal{Q}^{\pi}(s,a) = [r(s) + \gamma \sum_{s' \in \mathcal{S}} T(s^{'}|s,a) \sum_{a \in \mathcal{A}} \pi(a^{'}|s^{'}) \mathcal{Q}^{\pi}(s^{'},a^{'}), x_i, p_t, \mathcal{U}_i, s_i, g_i] \tag{6}$$

The parameters are defined below:

- Grid and customer are the players of the decision making process. Grid acts as one player, and customer acts as another player.
- s denotes different states of the system. In the proposed model, the states are as follows: on-peak, mid-peak, off-peak. On-peak hour denotes that the demand is higher than the supply. Mid-peak and off-peak hours denote that demand is moderate, and very low with supply, respectively.
- The set of actions of customer i are presented as $a \in \{\mathcal{E}_i, (\mathcal{E}_i + g_i), (\mathcal{E}_i + s_i + g_i), (s_i + g_i)\}$. Therefore, customer has four actions to decide his/her strategy — (a) grid energy; (b) grid and self-generated; (c) grid, storage, and self-generated; (d) storage and self-generated energy.
- T is transition probability matrix for reaching state $s^{'}$ from s by taking action a. The transition probability only depends on previous state, and thus, satisfies Markov properties. T can be defined as:

$$T^a_{ss'} = T[s^{'}|s, a] \tag{7}$$

and can be expressed as:

$$T = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix} \tag{8}$$

- γ is discount factor that the customer receives from the grid by choosing different states. γ also depends on the availability of storage and self-generated energy of the customer.
- The strategy of a customer corresponds to the demanded energy, $x_i \in \mathcal{X}_\mathcal{N}$ from the grid, satisfying the condition in Equation (4).
- p_t is the real-time price decided by the grid.
- $\mathcal{U}_i$ is the utility function of Player i that captures the benefits of the Player by making strategies.
- s_i is the storage energy, and g_i is the self-generated energy of Player 2.

1) Utility function of the customer: The utility function of the customer can be defined as $\mathcal{U}^c_i(x_i, p_t, s_i, g_i, \mathcal{E}_t, p_{si}, \gamma)$, where s_i is the storage energy, g_i is the self-generated energy, and $\mathcal{E}_t$ is the grid energy. Additionally, p_{si} is the satisfactory price of the customer i, and γ is the discount factor. For example, a customer i (where $i \in \mathcal{N}$) has lower satisfactory price (p_{si}) if he/she has higher storage and self-generated (energy) profile. Thus, the utility function for customer is non-decreasing with more storage and self-generated energy. Thus, the customer has to consume less energy from the grid. This can be expressed as:

$$\frac{\partial \mathcal{U}^c_i(x_i, p_t, s_i, g_i, \mathcal{E}_t, p_{si}, \gamma)}{\partial (s_i, g_i)} \geq 0 \tag{9}$$

The customer will be interested to consume less energy from the grid to maximize the payoff, and, thus, the utility of the customer can also be written from Equation (9) as:

$$\frac{\partial \mathcal{U}_i^c(x_i, p_t, s_i, g_i, \mathcal{E}_t, p_{si}, \gamma)}{\partial x_i} \leq 0 \tag{10}$$

The utility of the customer decreases with higher satisfactory price (p_{si}) as well as with higher real-time price (p_t) decided by the grid. Hence, the utility also can be expressed as follows:

$$\frac{\partial \mathcal{U}_i^c(x_i, p_t, s_i, g_i, \mathcal{E}_t, p_{si}, \gamma)}{\partial p_{si}} < 0 \tag{11}$$

$$\frac{\partial \mathcal{U}_i^c(x_i, p_t, s_i, g_i, \mathcal{E}_t, p_{si}, \gamma)}{\partial p_t} < 0 \tag{12}$$

Thus, we calculate the utility of the customer as follows:

$$\mathcal{U}_i^c(x_i, p_t, s_i, g_i, \mathcal{E}_t, p_{si}, \gamma) = (s_i + g_i)p_t - s_i c_{si} \tag{13}$$

2) Utility function of grid: The objective of the grid is to maximize its revenue. The grid decides the real-time price depending on the supply and demand from the customers. The utility for grid is also non-decreasing with an increase in the demand from the customers. Thus, the utility function can be expressed as:

$$\frac{\partial \mathcal{U}_i^g(p_t, \mathcal{X}_\mathcal{N}, \mathcal{E}_t)}{\partial \mathcal{X}_\mathcal{N}} \geq 0 \tag{14}$$

and the utility of the grid decreases with an increase in supply when demand is fixed. In such a scenario, the utility can be expressed as follows:

$$\frac{\partial \mathcal{U}_i^g(p_t, \mathcal{X}_\mathcal{N}, \mathcal{E}_t)}{\partial \mathcal{E}_t} \leq 0 \tag{15}$$

We calculate the utility of the grid as follows:

$$\mathcal{U}_i^g(p_t, \mathcal{X}_\mathcal{N}, \mathcal{E}_t) = \sum_i x_n(p_t - c_t) \tag{16}$$

This captures the total revenue of the grid when selling the energy required by all the customers. Here, $\mathcal{X}_\mathcal{N}$ is the total energy demanded from the customers, i.e., $\mathcal{X}_\mathcal{N} = \sum_i x_i$ and $i \in \mathcal{N}$.

B. Algorithm for the Decision Making Process

In order to make decision about the optimal strategies for both the customer and the grid, a small communication overhead exists between the customer and the grid. In this work, we propose two different algorithms, one for the grid and another for the customer. The customer makes a decision according to the satisfactory-price (p_{si}) and demanded energy (x_i), so as to maximize the pay-off. The customer, which has less demand, high storage, and self-generated energy, has higher satisfaction factor. On the other hand, the grid makes decisions about the real-time price (p_t) per unit energy, depending on the real-time demand to maximize the profit.

1) Algorithm for the grid: The grid receives the requested energy (x_i) from the customer, and calculates supply and total requested energy ($\mathcal{X}_{\mathcal{N}} = \sum_{i=1}^{n} x_i, \;\; i \in \mathcal{N}$) from customers. Depending on this demand and supply, the grid fixes a real-time price (p_t) per unit energy, and sends to the customer. It, then, receives the acknowledge from the customer, about whether the price (p_t) is within the satisfactory price (p_{si}) of the customer or not. If it is, then energy exchange takes place between the customer and the grid. Otherwise, according to modified energy demanded by the customer, the grid calculates its utility, $\mathcal{U}_i^g$, and sends the modified price (p_t^*) to the customer. Then energy exchange takes place between the grid and the customer. The grid sends the information to the customer to wait for the next time if again the modified price (p_t^*) is not within the satisfactory-price (p_{si}), and so on.

Algorithm 1 Algorithm for grid

Inputs: Requested energy (x_i) from the customer, total supply $(\mathcal{E}_t)$, total demand $(\mathcal{X}_{\mathcal{N}})$.
Output: The real-time price (p_t) per unit energy to maximize revenue.

1: Calculate total supply $(\mathcal{E}_t)$, and total demand $(\mathcal{X}_{\mathcal{N}})$
2: **if** $\sum_{i=1}^{n} x_i \leq \mathcal{E}_t$ **then**
3:     Advertise real-time price (p_t) per unit energy according to Equation (5)
4:     **Repeat Step** 6 to 11
5:     **if** $p_t \leq p_{si}$ **then**
6:         Exchange energy (x_i) with the customer
7:     **else**
8:         receive modified demand $(x_i = x_i^*)$ from the customer
9:         modify the price (p_t^*) according to Equation (5)
10:     **end if**
11: **else**
12:     Send information to the customer to wait
13: **end if**

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2) Algorithm for the Customer: Initially, the customer requests the grid for the total energy required (x_n), and receives the real-time price (p_t) information from the grid. He/she consumes energy if p_t is within the satisfactory-price (p_{si}). Otherwise, the customer calculates the storage (s_n) and self-generated energy (g_n) if available. Then the requested energy to the grid is calculated as $x_n^* = (x_n - (s_n + g_n))$. The customer receives the modified price (p_t^*) from the grid. He/she consumes the required energy if p_t^* is within the satisfactory-price (p_{si}); otherwise, waits with the waiting time.

Algorithm 2 Algorithm for Customer

Input: Required energy (x_i), satisfactory price (p_{si}), storage (s_i), self-generated energy (g_i).
Output: Maximize the pay-off and fulfill energy requirement

```
Send request to grid for required energy (x_i)
Receive real-time price (p_t) information from the grid
if p_t ≤ p_si then
    Exchange energy from the grid
else
    Calculate storage energy (s_i) and self-generated energy (g_i)
    if (s_i + g_i) ≤ x_i then
        requested energy (x_i^*) = x_i − (s_i + g_i)
        Receive some discounts (γ)
        Consume energy from the grid (x_i), storage (s_i) and self-generation (g_i)
        C_φ = [(x_i^*) ∗ (p_t − γ)] + s_i c_si
    else
        Exchange total energy from the grid
    end if
end if
```

V. Result and Discussion

To simulate the overall scenario, we use the simulation software built in MATLAB. The demand from the customer is randomly chosen, in such a way that it is less than or equal to 70 KWh. Also, the storage energy and self-generated energy are randomly generated, as shown in Table II. We create a transition probability matrix, as discussed in Section IV-A. The customer decides to choose different states and actions from the transition probability matrix, and makes strategies in order to maximize the pay-off. We assume the values of predefined constants in Equation (5) as $\alpha \geq 0$, $\beta \geq 0$, and $c \geq 0$. Table II shows the list of simulation parameters used to evaluate the results for proposed scheme.

We evaluate the performance of the proposed scheme, while comparing the existing literature with the availability of grid and storage energy. Therefore, the proposed scheme is compared with Ibars et al. model [7], while the customer has grid and storage energy facility. The performance of the proposed scheme is evaluated with different performance metrics — energy supply-demand, real-time price, cost, and utility.

TABLE II: Simulation Parameters

Parameter	**Value**
Number of customer	1
Number of utility provider	1
Storage energy (s_n)	$\leq$ 30 KWh
Self-Generation (g_n)	$\leq$ 40 KWh
Required energy (x_n)	$\leq$ 70 KWh

A. Supply and Demand Comparison

We calculate the customer's required energy (x_i), storage energy (s_i), and the demanded energy (x_i^*) to the grid. Supply and demand comparison is shown in Fig. 2 with respect to time. We assume that when the customer gets satisfactory price (p_{si}) from utility, then he/she consumes total required energy (x_i) from the grid, and, thus, x_i^* equals x_i.

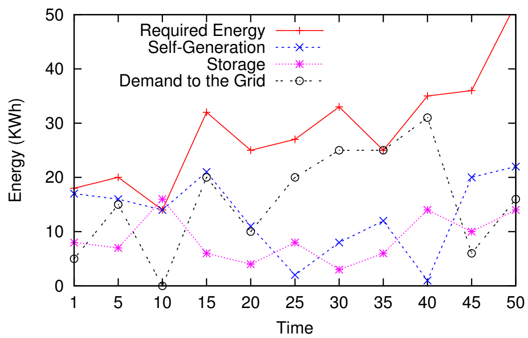


Fig. 2: Supply and Demand comparison wih Time

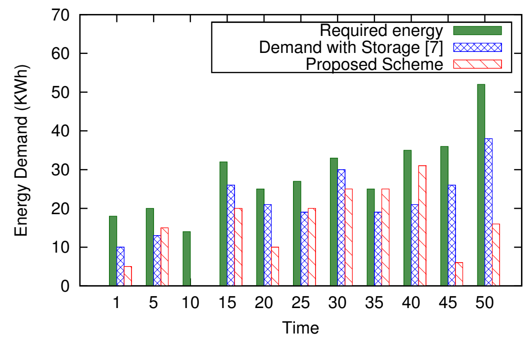


Fig. 3: Different demands to the grid

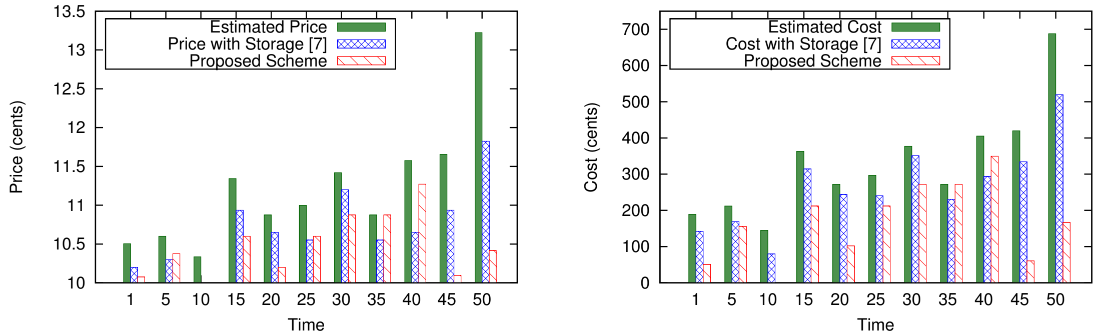
In Figure 3, we show the comparison of the required energy of the customer, and requested energy to the grid with the availability of different energy sources in different time instants. We see that the requested energy to the grid is always less than or equal to the required energy of the customer. Thus, the load on the grid is relieved, and, thus, grid provides a reliable energy supply to the end users. Additionally, with the presence of self-generated energy, customers' demanded energy is also reduced, which in turn minimizes the energy cost, which is discussed in Section V-B.

B. Price Comparison

We compare the real-time price decided by the grid. The cost incurred by the customer according to the demand (as shown in Figure 3) to the grid is shown in Figure 4. In Figure 4(a), we show the price comparison between using only grid energy and using the combined grid, storage, and self-generated energy. We see that if the customer uses energy by making decisions about the grid, storage and self-generated energy, then less price will be paid by the customer with efficient power distribution. So, our approach gives better result in order to maximize the customer's pay-off.

C. Total Cost Comparison

We calculate the total cost incurred by the customer with time. In Figure 5, we show the comparison of total cost in two different scenarios. In one scenario, the customer has only grid energy to use, and there is no decision



(a) Price comparison

(b) Cost comparison

Fig. 4: Price and cost using only grid energy and using grid, storage and self-generated energy

taken by him/her. Whereas, in another, the customer has three options: grid, storage and self-generation, and uses the energy by taking decision. We see that the customer saves huge amount of money with efficient energy supply in the presence of stored, and self-generated energy sources by making decisions.

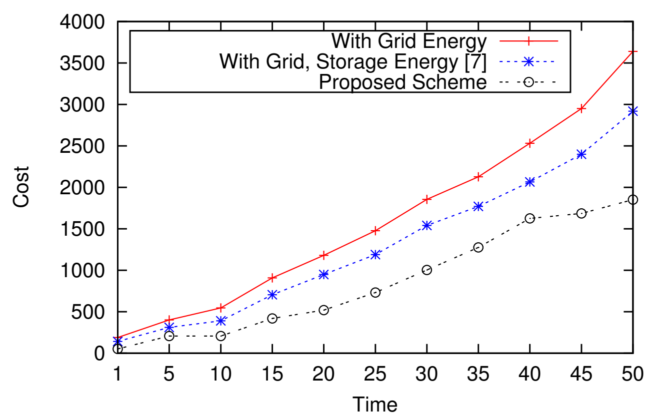


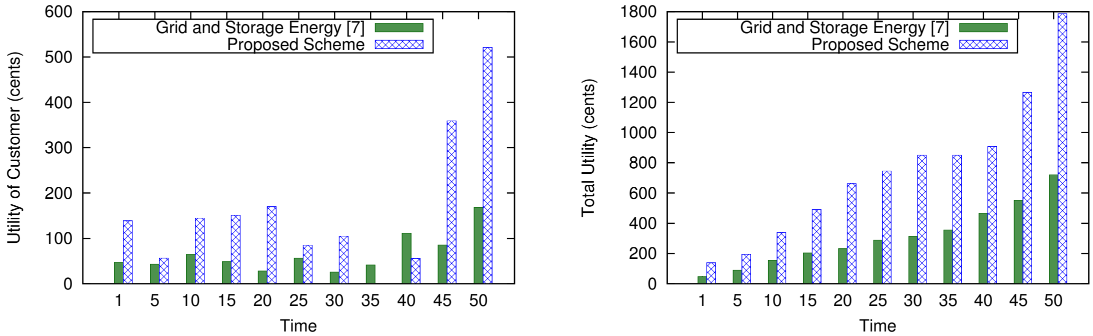
Fig. 5: Total cost comparison using only grid energy and using grid, storage and self-generated energy

D. *Utility of Customer*

We also calculate the utility function of customer in different states, i.e., with only grid energy and with all the energy sources. We calculate the utility function of the customer from Equation (13) and expressed as:

$$\mathcal{U}_i^c[x_i^*, s_i, g_i, \mathcal{E}_t, p_{si}, \gamma] \geq \mathcal{U}_i^c[x_i, \mathcal{E}_t, p_t] \quad (17)$$

Figure 6 shows the utility obtained by the customer with different energy sources. In Figure 6(a), the utility of customer with time is shown. When s_i and g_i are both not available, or the customer receives satisfactory-price (p_{si}) from the utility provider, the utility of the customer in both the states gives the same result. Otherwise, we see that using our approach, the utility of the customer increases. We also demonstrate the total utility obtained by the customer in Figure 6(b). We see that the customer gets more profit with an increase in the time period.



(a) Utility of customer at different time

(b) Total utility of customer

Fig. 6: Utility of customer

VI. Conclusion and Future Work

In this paper, we have proposed an MDP-based approach to study the customers' decision for energy cost optimization in order to maximize the customer's utility. Based on this optimization approach, we have shown how the customers can get the benefit from this decision making process, and also we see that the total expenses can be reduced. We have proposed the decision process of one customer to one source, where one customer has no information about the energy consumption behavior of the other customers. Future extension of this work includes how the decision process can be formulated using more than one customer, so that the customer can achieve more reliable and efficient service with maximization of the pay-off.

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