Residential Energy Management in Smart Grid: A Markov Decision Process-Based Approach

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***Abstract*—The deployment of advanced information and communication technologies has helped in the transformation of the traditional power grids into smart grids by introducing demand side management in residential area. The use of demand side management in the residential area can successfully reduce customer's energy consumption, and can also provide a well balanced energy demand throughout the day. Based on real-time pricing information, a customer can shift his/her energy demand to reduce the energy consumption cost. In this paper, we present a Markov Decision Process (MDP)-based scheduling mechanism for residential energy management (REM) in smart grid. The aim of the proposed work is to reduce the energy expenses of a customer. In this mechanism, the Home Energy Management Unit (HEMU) acts as one of the players, the Central Energy Management Unit (CEMU) acts as another player. The HEMU interacts with the CEMU to fulfill its energy request within its desired budget. The CEMU follows its own dynamic pricing mechanism to decide the price per unit energy for on-peak and off-peak hours. The proposed mechanism is able to reduce the energy expenses of the residential customers.**

***Index Terms* — Energy management, Extensive game, Smart Grid, Scheduling, Residential, HEMU, CEMU.**

I. Introduction

Electricity plays a crucial role in the development of a nation. With the increasing population, electricity demand is also increasing continuously. According to [1], by 2020, there will be a 75% increase in the electricity consumption. To fulfill this growing demand of power, power grid cannot rely only on traditional power plants. It should include renewable energy sources [2] as well as modern technologies to control energy consumption to balance the energy demand and supply. The electricity delivery network [3] consists of two sub-systems. The transmission system, acting as one of the sub-systems, delivers electricity from generation units to distribution substations. On the other hand, the distribution system, acting as another sub-system, delivers electricity from the distribution substations to the end users. A smart grid [4]–[7] delivers electricity from the supplier side to the customer side by using modern digital technology to reduce the customers' energy consumption [8], and save energy. By including advanced technology and communication [9], smart grid increases the reliability, and transparency in the entire electricity delivery system. One of the important features of smart grid is the demand response mechanism [10], [11], which offers customers the flexibility of tailoring their energy demand. A traditional power grid only employs demand response in larger scale customers, but for small-scale residential customers, no such facility is available. A smart grid [12], [13] also facilitates the employment of such facilities in a residential area. As a smart grid integrates advanced technologies and supports two-way information flow, it is possible for a smart grid to enable demand-side management [14], [15] in a residential area.

Residential energy management (REM) in smart grid has emerged as an attractive research field. For residential energy management [16], [17] in a smart grid, customers can actively participate in the system, and can tailor their energy consumption. With the help of smart meters, residential customers can get the information about their energy consumption, and using an assortment of energy management techniques, they can schedule their energy demand in order to reduce the energy consumption cost. Besides, if a large section of a residential customers start using these energy management techniques, then a well balanced load curve can be maintained throughout the day. These techniques not only help the customers, but also do so for the suppliers to avoid situations such as excess energy generation or energy wastage.

In this paper, we propose an intelligent residential energy management scheme based on Markov Decision Process (MDP). We introduce two energy management units — central energy management unit (CEMU), and home energy management unit (HEMU). We study the interaction between CEMU and HEMU. The CEMU decides the real-time price based on the total requested energy by all the HEMUs. The HEMU decides the price range according to the supplied energy and requested energy.

The rest of the paper is organized as follows. We briefly present the related literature in Section II. Section III describes the system model. In Section IV, we formulate the stochastic optimization method using MDP [18], and we discuss its properties. We also propose a distributed algorithm and discuss the performance of the algorithm in Section V. Finally, we conclude the paper while citing few research directions in Section VI.

II. Related Works

Demand side management allows the control of energy demand. A smart grid has the flexibility of applying demand side management for small-scale users in residential as well as industrial areas. There are several existing literature related to the energy management in smart grid [19]–[29]. Some of those are discussed below.

In [19], the authors discussed opportunities and challenges of deployment of WSN in a smart grid, and an experimental study on the statistical characterization of the wireless channel in different electric-power-system environments. In [21], the performance of the in home energy management (iHEM) is evaluated, and the authors also compared the evaluated results with the optimization based residential energy management (OREM) scheme. The authors claimed that their proposed approach works well for cost-effective energy management. They evaluated the performance of the proposed system in three performance metrics — real-time pricing, local energy generation, and priority based appliances. The authors also claimed that the communication delay, and the packet delivery ratio are decreased. In [22], Samadi et al. proposed a shared energy source for several subscribers, from where the customers consume the energy. The customers appliances are connected to a local area network as well as to the grid. They proposed an energy consumption controller (ECC), and all the appliances are equipped, and controlled with this controller. The authors also proposed a real-time pricing algorithm for energy management. They introduced their proposed approach in two ways — subscriber preference model, and distributed algorithm for interaction between smart meter and service provider. In [24], the authors introduced a coordination scheme for reducing the cost of energy consumption, and this scheme is called appliance coordination (ACORD) scheme. The ACORD scheme shifts the shift-able devices to the off-peak hours to reduce the cost for energy consumption. The authors claimed that their approach significantly reduces the home energy cost. In [28], the authors proposed a shared energy source that is called energy consumption scheduling (ECS) devices. The smart meter requests energy to the ECS, and accordingly, the ECS acts as an automated demand side management device. The smart meter, and ECS interact autonomously with the implementation of a distributed algorithm. The authors claimed that their proposed approach reduced the peak-to-average (PAR) ratio according to the simulated results. In [29], Nguyenet al. proposed a demand side management scheme to reduce the energy consumption cost. In this scheme, the service provider updates the real-time price according to the real-time demand on the grid. They designed their proposed algorithm as game theoretic methods to optimize the total energy cost.

III. System model

In Figure 1, the schematic view of a typical residential power system is shown. In a residential power system, several central energy management units (CEMUs) exist. A CEMU works as a energy management unit of a service provider. A service provider supplies electric energy to a group of customers in the smart grid. Hence, under a CEMU, several home energy management units (HEMUs) exist. A HEMU works as an energy management unit of a customer. The HEMU requests energy to the CEMU at different time according to necessity of the customer. Let us consider a residential power system with M number of CEMUs. A CEMU, $j \in M$, consists of N_j number of customers. Several appliances may exist in a customer's house. We denote that as an appliance, $k \in A_i$, belongs to customer, $i \in N_j$. So, if an appliance, $k \in A_n$, requires e_k amount of energy, and the customer has a total of A_n appliances, then the customer requests a total energy of amount x_n. Mathematically,

$$\sum_{k \in A_n} e_k = x_n \tag{1}$$

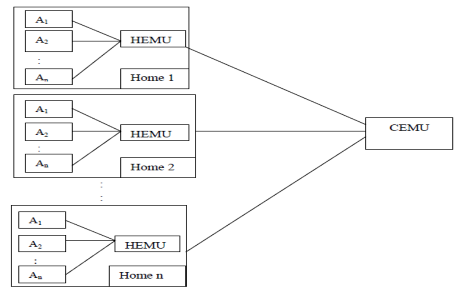

Fig. 1: The model of the schematic residential power system

Hence, the HEMU of a customer, $n \in N_j$, schedules its appliances or tasks with a minimum energy consumption cost. In order to do so, the HEMU communicates with the CEMU. Now, at a time, several HEMUs will request a CEMU to schedule their task based on communication. The HEMU sends a request to the CEMU having some parameter such as total amount of energy, x_n, request preference, request waiting time, and desirable cost. The request preference indicates the urgency to turn on an appliance. The CEMU sends a request having a price range that indicates the range within which a CEMU will set the per unit price. The HEMU interacts with the CEMU in order to know the specific period and the duration within which the appliances must be served for avoiding the on-peak hour of a day. After getting all the requests from all the HEMUs, the CEMU schedules those requests using Markov decision process (MDP).

IV. Proposed MDP-based scheduling approach

A. Game formulation

To study the interaction between the HEMU and the CEMU, we use MDP to make the decision process [30]–[33]. In Figure 2, we can observe the nature of communication between the HEMUs and the CEMUs. We consider a HEMU as player 1, and a CEMU as player 2. Based on the request of player 1 (HEMU), player 2 (CEMU) chooses its strategy, and so on. This game is defined in its strategic form as follows:

$$\tau = [(M \cup N), (U_n)_{n \in N}, (U_c)_{c \in M}, (X_n)_{n \in N}, (C)_{c \in M}, (e)_{c \in M}]$$

where, the CEMU in M acts as a player, and the HEMU in N acts as an another player. U_n is the utility function for the n^{th} HEMU, and U_c is the utility function for c^{th} CEMU.

Utility function for a HEMU: For every HEMU, $n \in N$, we define the utility function $U_n(x_n, x_{-n}, x_p, ai, p^t)$, which represents the level of willingness of HEMU to get served early. Here, x_n represents the demanded energy of n^{th} HEMU, x_p represents the appliance's preferences, ai denotes the appliance's iteration number, and p^t denotes the price per unit

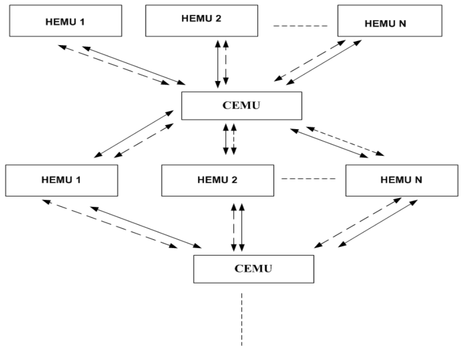

Fig. 2: Schematic Diagram of MDP-based multilevel decision making process

energy. Therefore, the properties that the utility of a HEMU must satisfy are as follows:

i) The utility function U_n of the HEMU is directly proportional to the preference of the appliances, x_p. If the preference of appliance i is higher than the preference of appliance j, i.e., $(x_p)_i > (x_p)_j$, then $(U_n)_i > (U_n)_j$. Mathematically,

$$\frac{\partial U_n(x_n, x_{-n}, x_p, ai, p^t)}{\partial x_p} \geq 0 \tag{2}$$

ii) The utility function U_n of the HEMU is directly proportional to the iteration of appliances, ai. If the iteration of the appliance i is higher than the iteration of appliance j, i.e., $ai_i > ai_j$, then $(U_n)_i > (U_n)_j$. Mathematically,

$$\frac{\partial U_n(x_n, x_{-n}, x_p, ai, p^t)}{\partial ai} \geq 0 \tag{3}$$

iii) The utility function U_n of the HEMU is inversely proportional with price, p^t. If the i^{th} HEMU pays greater price for the same amount of energy than the j^{th} HEMU, i.e., $p_i^t > p_j^t$, then $(U_n)_i < (U_n)_j$. Mathematically,

$$\frac{\partial U_n(x_n, x_{-n}, x_p, ai, p^t)}{\partial p^t} < 0 \tag{4}$$

Therefore, we consider the following specific utility:

$$U_n(x_n, x_{-n}, x_p, ai, p^t) = x_n x_p + x_n ai - x_n p^t \tag{5}$$

Utility function for a CEMU: For every CEMU, $c \in M$, we define the utility function $U_c(x_n, x_{-n}, C, r, ex, p^t)$, which represents the level of willing of CEMU to serve the task requested by a HEMU. Here, x_n represents the demanded energy by the HEMU, $n \in N$, C denotes the total energy capacity of the CEMU, r denotes the remaining total request, and ex represents the excess energy of the CEMU, $c \in M$. p^t is the price per unit energy decided by the CEMU. Therefore, the properties that the utility of a CEMU must satisfy are as follows:

i) The utility function of the CEMU, U_c, is directly proportional to the energy capacity of the CEMU, C. If the capacity of the k^{th} CEMU is higher than the capacity of the l^{th}, i.e., $C_k > C_l$, then $(U_c)_k > (U_n)_l$. Mathematically,

$$\frac{\partial U_c(x_n, x_{-n}, C, r, ex, p^t)}{\partial C} \geq 0 \tag{6}$$

ii) The utility function of the CEMU, U_c, is inversely proportional to the remaining energy request to be served, r. If the remaining energy request of the k^{th} CEMU is higher than the remaining energy request of the l^{th}, i.e., $r_k > r_l$, then $(U_c)_k < (U_n)_l$. Mathematically,

$$\frac{\partial U_c(x_n, x_{-n}, C, r, ex, p^t)}{\partial r} < 0 \tag{7}$$

iii) The utility function of the CEMU, U_c, is inversely proportional with the excess energy, ex. If the excess energy of the k^{th} CEMU is higher than the excess energy of the l^{th}, i.e., $ex_k > ex_l$, then $(U_c)_k < (U_n)_l$. Mathematically,

$$\frac{\partial U_c(x_n, x_{-n}, C, r, ex, p^t)}{\partial ex} < 0 \tag{8}$$

iv) The CEMU modifies the price per unit energy, p, so that the CEMU gets maximum profit. Mathematically,

$$\frac{\partial U_c(x_n, x_{-n}, C, r, ex, p^t)}{\partial p^t} \geq 0 \tag{9}$$

$$U_c(x_n, x_{-n}, C, r, ex, p^{t*}) \geq U_c(x_n, x_{-n}, C, r, ex, p^t) \tag{10}$$

where p^* is the modified price decided by the CEMU.

Therefore, we consider the following specific utility function,

$$U_c(x_n, x_{-n}, C, r, ex, p^t) = x_n C + x_n p - x_n r - x_n ex \tag{11}$$

where $x_n \in [0, C]$, and $x_{-n} = [x_1, x_2, .., x_{n-1}, x_{n+1}, .., x_N]$

Dynamic Pricing Model: In our proposed model, we use the dynamic pricing model, i.e., the price per unit energy for individual customer is decided according to their requested energy. Let, the price per unit energy for HEMU, n, is p_n^t at time t, where $n \in N$. The real-time price function for the HEMU n is defined as follows [34],

$$p_n^t = a + b + c{x_n^t}^2 \tag{12}$$

where, a, b, and c are constants, and x_n^t is the individual demand for HEMU n at time t.

From the Equation 12, it is evident that, if the HEMU n requests a larger amount of energy to the CEMU, then the CEMU decides higher price per unit energy for that HEMU n, and vice versa.

B. Proposed Algorithm

In this paper, we present an energy scheduling algorithm for a small number of residential customers. The residential area consists of a small number of customers and a service provider. The customer, and the service provider have the energy management units which exchange information for energy scheduling. Whenever, the customer needs to schedule his energy request, s/he sends the request to the service provider, i.e., CEMU. Based on the received energy demand requested from HEMUs, a CEMU decides, or updates its current price per unit energy. After getting the price decided by the CEMU, the HEMU decides whether to serve with that price, or wait for a reduced price. We proposed two different algorithms — one for the HEMU, and another for the CEMU.

1) Algorithm for HEMU: Each HEMU, $n \in N$, calculates the total energy requirement by adding up the energy requirements by the appliances, e_k, of that customer, $n \in N$. Mathematically,

$$x_n = \sum_{k=1}^{A_n} e_k$$

Now, the HEMU requests the CEMU to serve its energy requirement, x_n. The CEMU calculates total energy requested by the HEMUs, and decides the price per unit energy. Hence, if the price is within the range of a HEMU decided by the customer, then the HEMU requests the CEMU to serve the energy request. Otherwise, the HEMU waits for a certain time, and requests the CEMU again.

Algorithm 1: Algorithm for HEMU

Input: Price per unit energy, p^t, decided by the CEMU, $c \in M$;
Output: Requested energy, x_n, by the HEMU, $n \in N$;
if *Price decided by CEMU* (p^t) $<$ *Desired cost of the HEMU* (d) **then**
  evaluate $x_n = \sum_{k=1}^{A_n} e_k$;
  Request the CEMU, $c \in M$, to serve the required energy, x_n;
else
  Modify the value of requested energy, x_n, by dropping the request of the appliance with lowest priority;
  Calculate the modified value of x_n, i.e., x_n^*, such that,
  $x_n^* = \sum_{k=1}^{A_n - 1} e_k$, and
  $U_n({x_n}^*, x_{-n}, x_p, ai, p^t) \geq U_n(x_n, x_{-n}, x_p, ai, p^t)$

2) Algorithm for CEMU: The service provider maintains the algorithm of the CEMU. The CEMU gets the requested energy from different HEMUs, and calculates the total energy requested to the CEMU, X_c. Mathematically,

$$X_c = \sum_{n=1}^{N} x_n$$

If the total requested energy to the CEMU is less from the capacity of the CEMU, C, then the CEMU serves the requested appliances, as the HEMU already approved to be served with the price, p^t, decided by the CEMU. Otherwise, the CEMU drops the requests of the appliances having lowest priority, and sends the requests in the waiting state. The CEMU also informs the HEMU that its requests are in the waiting state.

Algorithm 2: Algorithm for CEMU

Input: Requested energy, x_n, by the HEMU, $n \in N$;
Output: Price per unit energy, p^t, decided by the CEMU, $c \in M$;
if $\sum_{n \in N} x_n < C$ **then**
  Distribute the requested energy by the HEMU, $n \in N$;
  Modify the price per unit energy, p^t, so that,
  $U_c(x_n, x_{-n}, C, r, ex', p^{t*}) \geq U_c(x_n, x_{-n}, C, r, ex', p^t)$
  where ex' is the modified remaining energy of the CEMU;
else
  Discard the request with lowest preferences, and inform the HEMU whose request has been discarded;

V. Results and Discussions

For simulation purpose, we have used MATLAB. In our model, we assumed that the residential area consists of 10 customers, i.e., 10 HEMUs, and one CEMU. We considered two scenarios — fixed appliances, and variable appliances, that request the CEMU to serve their energy requirements, based on the random parameters as shown in the TABLE I.

Requested Energy unit	1-5
Request Preference	1-3
Request waiting time	1-6
Desirable cost	2-8
Price range of CEMU	2-8

TABLE I: Simulation Parameters

We executed the simulation 15 times, and the graphs are plotted using the 95 % confidence interval.

Daily cost for each HEMU: In Figure 3, we shown the results using EMU (Energy Management Unit), and without using EMU. In our model, each residential customer has an energy management unit, which is termed as HEMU, and the service provider's EMU is termed as CEMU. We can see that, with the EMU deployment, the customers are charged with less cost than without the EMU deployment. In Figure 4, we show the daily cost for each customer with, and without EMU deployment, while each customer has different number of appliances.

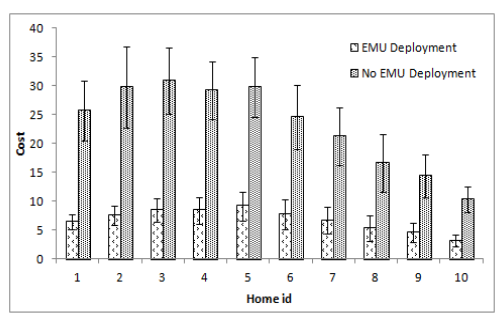

Fig. 3: Daily cost for each HEMU with fixed appliances

Waiting time for each HEMU: Each customer sends an energy request with the waiting time as a parameter. The comparison between the preset waiting time, i.e., the maximum time for the customer, s/he can wait for a service, and the actual waiting time, i.e., the customer actually waits to get served, is

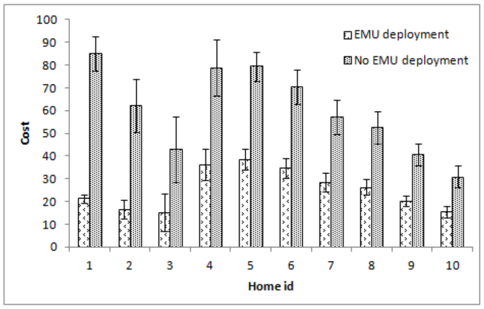

Fig. 4: Daily cost for each HEMU with varying appliances

shown in Figure 5. From Figure 5, it is clear that without even waiting for the maximum time, the customers get serviced. Figure 6 shows the comparison between the actual waiting time, and the maximum waiting time, when the customers have different number of appliances.

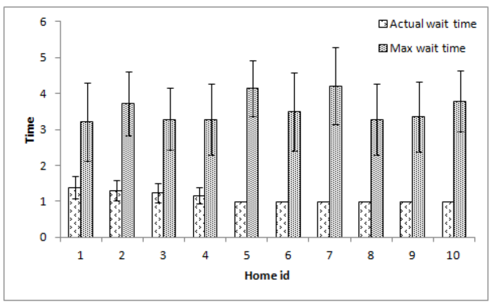

Fig. 5: Waiting time for each HEMU with fixed appliances

Actual cost Vs desirable cost for each HEMU: In Figure 7, we show the comparison between actual cost, and desirable cost. The desirable cost is the range provided by the customer, and the actual cost is the cost that the customer pays for his/her energy request. The customer does not want his/her actual cost to exceed the desirable cost. Our results show that customers pay equal or less money than the desirable amount. In Figure 8, we show the comparison between the actual cost, and the desirable cost, when the HEMUs have different number of appliances.

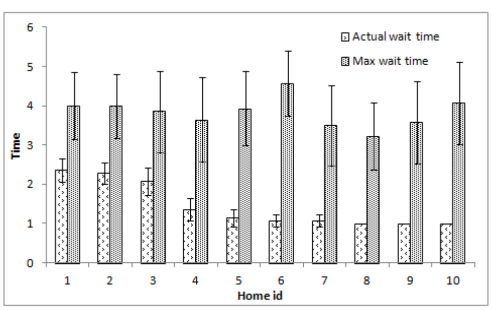

Fig. 6: Waiting time for each HEMU with varying appliances

Cost comparison between EMU and ECS: Few other pieces of existing literature [28] have also worked on a similar nature of problem. Here, we have compared the pricing model of our algorithm with the implementation of the algorithm, as per our understanding, proposed by the authors in [28], termed as energy consumption scheduling (ECS). The corresponding results are presented in Figure 9. Here, our proposed algorithm is termed as energy management unit (EMU). It is evident that our solution provides a less daily cost to the customers compared to the other one. In Figure 10, we show the comparison between the cost to be paid by the customer with varying alliances.

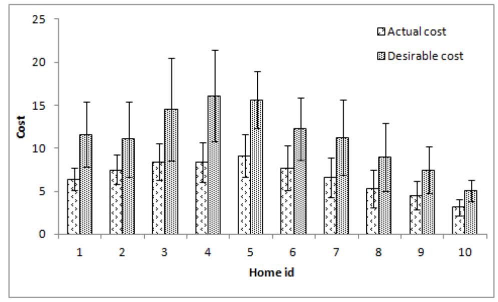

Fig. 7: Actual cost vs desirable cost for each HEMU with fixed appliances

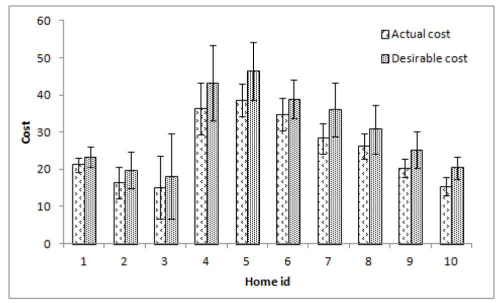

Fig. 8: Actual cost vs desirable cost for each HEMU with varying appliances

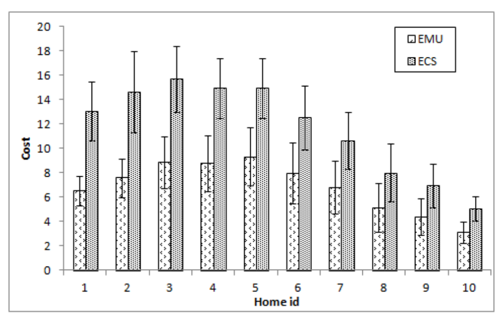

Fig. 9: Cost comparison for each HEMU with fixed appliances

VI. Conclusion

In this paper, we have formulated the MDP-based approach to schedule the appliances for residential energy management. Based on the proposed algorithm, we showed how the appliances can be scheduled using the HEMUs and the CEMUs. The simulated results show that we can improve the scheduling performance with the help of a energy management unit (EMU). Future extension of this work can be done by considering one HEMU connected with several CEMUs, that

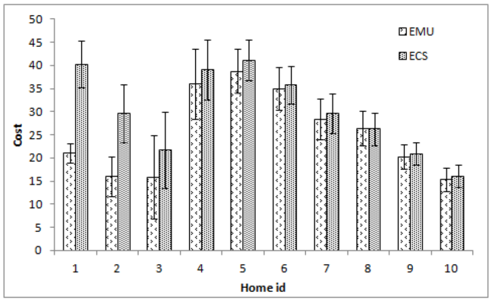

Fig. 10: Cost comparison for each HEMU with varying appliances

will help to reduce the peak load over the network as well as for different CEMUs.

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