# Effective Load Scheduling in Distributed Demand Response Framework using ADMM

Rishabh Verma, *Member, IAENG,* Rajesh Kumar, and Shalini Pal

***Abstract*—The smart grid is a self-employed future generation electricity grid. The demand response programs have proved a valuable contribution towards the implementation of this future grid. With the help of advanced metering infrastructure, it becomes viable for home users to optimize their load with the rotation of real-time prices as well as minimize the cost incurred for their energy consumption. This paper presents a distributed load scheduling method for demand response programs in the framework of the smart grid. The distributed optimization approach has been carried out to optimize the cost of the user and load leveling for utility. This algorithm is implemented using alternating method of multipliers (ADMM) via parallel approach. The cost saving of users can improve the mechanism of the system and encourage other users to participate. The simulation result proves the efficiency of the proposed algorithm.**

***Index Terms*—Smart grid, demand response programs, real time pricing, advanced metering infrastructure, Lagrange multiplier.**

## I. Introduction

The rapid growth of energy demand has become a huge issue for the electricity grid. So, the smart grid has evolved to deal the with problems with the electricity grid. Electrical industry and people from academia have assessed the implementation of a smart grid to meet the forthcoming energy demand. Advanced technologies and communication techniques have emerged in smart grids to serve the future power system. The concept of smart grid has come up with the self-healing advancement, user accompanied approaches, and reliable methods for control of the electricity grid. The advanced metering infrastructure and smart meters have a key role in making smart grid implementation feasible [1] reviewed that the advantages of smart grid have enhanced the customer participation and reliable decisions in the electrical industry. Demand response (DR) programs are an integral part of the smart grid which accompanies the activity on the demand side of grid. The concept of demand response is associated with increasing customer involvement to minimizing the cost incurred on their energy usage. The US Energy Department has defined demand response as, “the customer electricity usage can be changed by variation in the electricity prices, or to induced lower energy usage in exchange for incentive payments at times of high market prices or system reliability is jeopardized” [2]. DR programs can be classified into two types: price-based DR and incentive-based DR. In price-based DR customer has given the option to schedule their energy consumption with different pricing options such as time-of-use pricing (TOU), critical peak pricing (CPP), and real-time pricing (RTP) tariff to get reduced energy bill [3]–[5]. Incentive-based DR programs regulate by providing customers some incentive to reduce their energy consumption at the time notification appears from the program sponsor. The contribution [6] of the work reflects that price-based programs are highly dependent on smart metering technology which allows bidirectional information communication between the user and energy provider company.

Manuscript received May 17, 2023; revised July 31, 2025.

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DR programs contribute a variety of monetary and operational benefits to the customers and energy providers. The electricity cannot be stored economically and the supply-demand balance should be maintained in the real system. With the regulation of DR programs home, customers have a chance to schedule their appliances in accordance to less electricity prices. In order to balance the supply-demand ratio the flattenned load curve can be achieved using the techniques of demand side programs. For encouraging the user to involved with DR programs TOU and RTP schemes play a vital role. In TOU pricing the day is divided into slots depending on peak and off-peak hours, followed by varying the prices in the slots. Whereas RTP gives customers hourly varying tariffs that reflect the value and price of energy for distinct time slots [7]. An artificial intelligence (AI) based household energy management is presented in [8], here a genetic algorithm is used as knowledge base AI to optimize energy consumption of houses on weekdays and weekends. However, the heuristic algorithm is not sufficient to mitigate uncertain load scheduling.

### A. Related work

The DR technologies have many approaches to explore the utilization of the sources and manage the demand. In the literature, authors have given different solution methods to recognize the DR problem from the perspective of residential users [9]. A wireless sensor network-based intelligent smart home energy management system named MinNet was developed in [10]. The implementation of a wireless sensor network for the purpose of appliance state monitoring and occupancy inference is done. The optimization problem is formulated for the optimal placement of sensors to estimate the on-off states of home appliances from aggregated and person occupancy in the room. A utility model is introduced to analyze the price elastic behavior of aggregated load from customers [11]. The social welfare maximization of consumers is calculated using the elasticity model without the excessive information change among consumers and utility companies.

A game theoretic approach is developed for the energy consumption scheduling of residential consumers [12]. The performance of the approach is analyzed regarding minimizing the usage costs to find the Nash equilibrium of the energy consumption game. A nonlinear time-based rates model is created to extract mathematical expressions for time-of-use (TOU) DR programs [13]. The demand side problem has been explored using different classical and heuristic optimization methods. In this context, author proposed a day-ahead load-shifting mechanism as a minimization problem using an evolutionary algorithm [14]. In this method, the peak load is shifted to off-peak hours to achieve the objective load curve which depends on the electricity price. They have considered a large type of smart grid serving three different areas for implementation purposes.

A home-to-grid algorithm is introduced to cut the peak energy usage of a household user [15]. In this algorithm, Baye's theorem is used to determine the probability of each appliance's energy consumption based on historical usage data. The algorithm result leads to cost reduction in domestic energy and reduces or even eliminates peak-hour energy consumption. In [16], the DR problem is solved using convex programming with home appliances load management. This method solved the formulated problem in terms $L_1$ regularization technique to solve a shiftable load of appliances in the form of a binary decision variable. The home energy management problem with PV generation, energy storage devices, and mixed types of home appliances AC and DC load is formulated in [17]. To investigate the behavior of batteries and characteristics of AC and DC conversion, the different comparison has been made which results in the increment in savings.

In the literature, the implementation of the most DR problems has been solved using centralized techniques. In a centralized manner, the user is not allowed to make their decision on their own. A centralized controller or utility will take the decision on behalf of the user. Whereas in the distributed optimization consumer are offered to make their own decision for load scheduling. The centralized framework does not provide privacy preservation of user information. To preserve privacy, a data privacy preservation model is proposed in [18], where the constraints-relaxed functional dependency method is approached. However, these methods produce more distortion in data, so the data is not utilized as required. Some authors in the literature have explored distributed optimization techniques. In this context, the author in [19] proposed a multiagent framework to solve the DR problem for heterogeneous homes. Different type of agents is considered such as home agents (HAs) and a retailer agent (RA) to evaluate distributed control algorithms for scheduling heterogeneous household electricity usage to improve energy efficiency. A distributed algorithm to solve the DR problem exists in [20] using the Newton method. A distributed algorithm to minimize the electricity bill of users with electric vehicle load scheduling in a smart grid is developed in [21]. In this work, the optimization is done using the alternating direction method of multipliers which results in fast convergence and optimal solution to the problem.

### B. Contribution to work

In this paper, some household user is registered for the price-based demand response program in the framework of the smart grid. Multiple energy user is supplied power by a utility company. A home area connection is made through the technology of advanced metering infrastructure. The connection between utility and user can also be made via a home automation wireless network based on Bluetooth devices [17]. A load of users is considered from historical load data. To avoid the limitation of a centralized manner for load scheduling optimization, the distributed algorithm is implemented for the purpose of minimizing user daily costs. In this work, the alternating direction method of multiplier (ADMM) is used to solve the optimization problem. This algorithm works in parallel form. This method can be advantageous to the user because they don't need to share their information with the utility. Which makes this system reliable and controlled to ensure user privacy. The ADMM guarantees the fast convergence of the problem and it can be easily implemented in practical cases.

The paper is organized into five sections. Section 2 presents the system model of energy multi-user with characteristic load. Section 3 discusses the problem description and proposed distributed algorithm. The simulation result of analyzing the given system model is presented in Section 4. Finally, the paper is concluded with future aspects in Section 5.

## II. System Model

In this system architecture, a utility company is supplying electricity to multiple user systems as shown in Fig 1. Each user is installed with an automatic load control unit (ALCU). It is assumed that the built-in smart meter is composed in ALCU. This unit can be used as a medium of communication between utility and energy users. Here each user is participating in the price-based DR program offered by the utility company. This system exhibits a distributed model in which users don't need to share their load information with the utility so that the privacy of users can be maintained. The user is allowed to make the scheduling decision through their ALCU system in which user preferences can also be sent. The different options are available for the user to participate in the DR programs. The different objectives have been built in ALCU for the sake of users. The ALCU receives the real-time price data from the gateway built for the residential by the utility and applies the DR algorithm to find out when and how to operate home appliances.

The proposed DR algorithm aims to automatically control the load of home appliances and optimize the benefit for users. The load of users and cost incurred by energy usage are optimized using a distributed DR algorithm. The objectives can be composed as follows,

- The reduction in peak demand of the load curve.
- Reduce the energy cost of energy bills.
- The regulation of energy efficiency in a household.
- Utilization of energy when electricity prices are low.

### A. Appliance load

The household user consists of distinct characteristic appliances. The home appliance can be classified into two main types as follows.

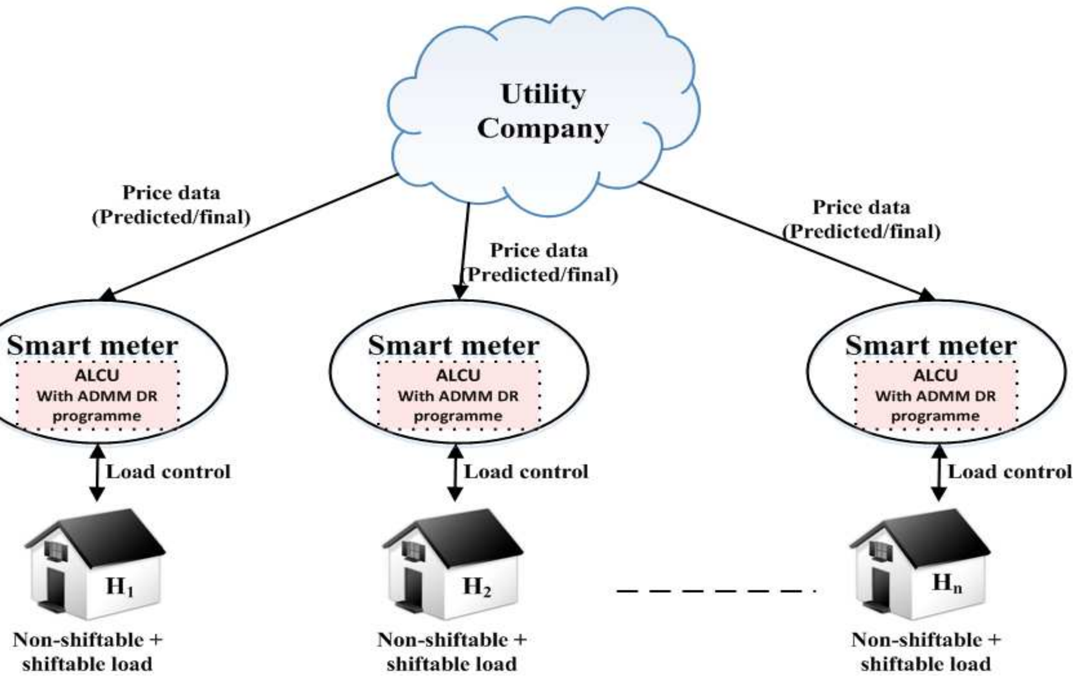


Fig. 1. DR system architecture

*1) Non-shiftable appliances:* The non-shiftable appliance is non-interruptible in nature. The load corresponding to the type of appliance is considered as base load of a household. It is necessary to fulfill their energy requirement as they can't be shifted to any other time slot. Even their load cannot be varied under any condition such as dynamic electricity prices.

*2) Shiftable appliances:* The shiftable appliances can be shifted from one to another time slot. These appliances have some minimum and maximum energy consumption limits during utilization. Shiftable appliances can be a time-shiftable and power-shiftable appliance. In time-shiftable their energy demand cannot be compromised but possible to shift from one slot to another as offered by the load scheduling mechanism. Power-shiftable appliances cannot be interrupted once start running, but their energy can be varied within a limit.

### B. Real time pricing (RTP)

The user is offered real-time prices from a utility for enrolling in the DR program. Users will get information on electricity prices for particular hours. In the past, several pricing models have been explored for household users. British Columbia (BC) Hydro and Power Authority has developed inclining block rates (IBR) [22]. BC Hydro and Power have announced the price of electricity as from $7.52$ Cents/kWh to $11.27$ Cents/kWh as per the energy usage of users. They price the user $7.52$ Cents/kWh as the first slot price when the two-month energy usage is less than $1350$ kWh, and the user pays to second installment price i.e. $11.27$ Cents/kWh if the limit exceeds.

In the power system, the energy demand is not static quantity and the storage comes with economic issues, which result in an imbalance supply-demand ratio. To meet the peak demand the different generation plants can be integrated, but their installment cost is high. To manage the peak demands the real-time pricing tariff has developed these days. With the help of real-time pricing, the load in peak hours can be reduced to a certain limit. In this paper, we have used RTP data from Ameren Illinois Corporation [23].

## III. Problem Formulation and Distributed Algorithm

### A. Electricity usage model for user

The problem of automatic load scheduling can be done in a various manner. Although the main objective is to maximize the savings on daily electricity bills that occur to users it minimizes the total electricity cost of the system. In this load scheduling an assumption is made that with the help of distinct prediction techniques embedded in the ALCU, it is able to predict the day-ahead load for each user. Then by implementing an algorithm embedded in ALCU, the electricity bill can be optimized via the load-shifting concept. The optimization problem for load shifting can be formulated under the following cases. In this paper, $N$ number of users is considered which is denoted by $n$, where, $n \in N$. Each user has some non-shiftable and shiftable kinds of appliances. This day-ahead load scheduling is taken for $24$ hour which is denoted by $t$. The total load of user $E_{n,t}$ can be written as follows,

$$E_{n,t} = E_{n,t}^{shiftable} + E_{n,t}^{non-shiftable} \quad (1)$$

where, $E_{n,t}^{non-shiftable}$ and $E_{n,t}^{shiftable}$ are non-shiftable and shiftable appliance load, respectively. The number of non-shiftable and shiftable appliance varies for each user in the system.

The concept of the load shifting technique is explained in Fig 2. The load shifting is done by transferring the load from high price hour to low price hour. The $x_{n,t}$ is the load shifting variable of $n^{th}$ user in hour $t$. The electric price in each hour is denoted by $P_t$. The objective function which depicts the load scheduling of energy users can be discussed in the following cases.

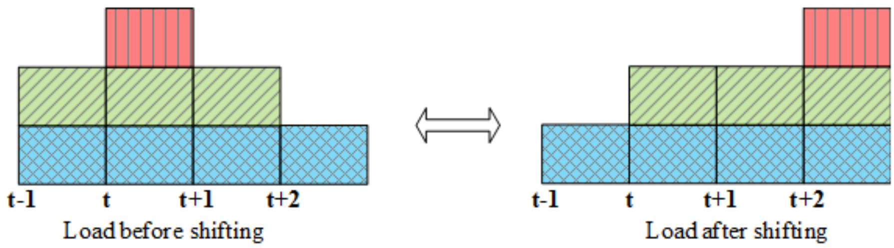


Fig. 2. Load shifting technique

*1) Case 1: Peak-to-Average Ratio (PAR) minimization:* In this case, the objective function for optimizing Peak-to-Average Ratio (PAR) minimization can be formulated in terms of the total load of the user. The non-shiftable load of the user is fixed during optimal load scheduling. Shiftable loads are loosely constrained for PAR minimization. Here only shiftable load can be user for load-shifting purposes. The objective function $PAR$ can be represented as follows.

$$\text{Minimize} \;\; PAR = \frac{Max\Big\{E_{n,t}^{non-shiftable} + x_{n,t}\Big\}}{Avg\Big(E_{n,t}\Big)} \qquad \forall n \in N \tag{2}$$

Subject to:

$$E_{n,t}^{shiftable,min} \le x_{n,t} \le E_{n,t}^{shiftable,max} \qquad \forall n \in N \tag{3}$$

$$\sum_{t=1}^{24} x_{n,t} = \sum_{t=1}^{24} E_{n,t}^{shiftable} \qquad \forall n \in N \tag{4}$$

The load shifting variable of each user is different, and it is calculated in a parallel iterative procedure. In this case, the aim of optimization is to shift a total load of user. The total cost occur on each user $C_n$ can be calculated as,

$$\mathrm{C}_n = \sum_{t=1}^{24}\Big(P_t * (E_{n,t}^{non-shiftable} + x_{n,t})\Big) \tag{5}$$

*2) Case 2: PAR minimization using additional load:* In this case, the objective function is made with additional load added with shiftable load. This objective can have more impact on the saving of user because of tightly constrained shiftable load regulates the load shifting process. The similar objective can be made as follows.

$$\text{Minimize} \;\; PAR = \frac{\Big(E_{n,t}^{shiftable} + x_{n,t}\Big)}{Avg\Big(E_{n,t}\Big)} \qquad \forall n \in N \tag{6}$$

$$\begin{aligned} \text{Subject to} \;\; A_n * x_{n,t} &= B_n && \forall n \in N \\ \sum_{t=1}^{24} x_{n,t} &= 0 && \forall n \in N \end{aligned} \tag{7}$$

where, $A_n$ is the coefficients of shiftable load and $B_n = 0$. The total cost of each user can be defined as:

$$\mathrm{C}_n = \sum_{t=1}^{24}\Big(P_t * (E_{n,t}^{non-shiftable} + E_{n,t}^{shiftable} + x_{n,t})\Big) \tag{8}$$

*3) Case 3: Cost minimization with real time price coefficient:* This case represents the optimization of total load for each user with respect to real time price coefficients. The optimization problem can be formulated such as,

$$\text{Minimize} \;\; f(x) = \sum_{t=1}^{24}\Big(P_t * (E_{n,t}^{non-shiftable} + x_{n,t})\Big) \qquad \forall n \in N \tag{9}$$

$$\begin{aligned} \text{Subject to} \;\; A_n * x_{n,t} &= B_n && \forall n \in N \\ \sum_{t=1}^{24} x_{n,t} &= \sum_{t=1}^{24} E_{n,t}^{shiftable} && \forall n \in N \\ E_{n,t}^{shiftable,min} \le x_{n,t} &\le E_{n,t}^{shiftable,max} && \forall n \in N \\ max(E_{n,t}^{non-shiftable} + x_{n,t}) &\le E_{n,t}^{max} && \forall n \in N \end{aligned} \tag{10}$$

Where $A_n$ is the coefficients of sum of total load and $B_n = E_{n,t}^{shiftable}$. The energy cost of each user is formulated as,

$$\mathrm{C}_n = \sum_{t=1}^{24}\Big(P_t * (E_{n,t}^{non-shiftable} + x_{n,t})\Big) \tag{11}$$

*4) Case 4: Cost minimization using additional load:* This case evaluates the performance of optimization for the cost saving formulation. Here the aim of optimization is centered around cost optimization of energy user which can be proven highly effective for bill saving of user.

Minimize:

$$f(x) = \sum_{t=1}^{24}\Big(P_t * (E_{n,t}^{non-shiftable} + E_{n,t}^{shiftable} + x_{n,t})\Big) \qquad \forall n \in N \tag{12}$$

$$\begin{aligned} \text{Subject to} \;\; A_n * x_{n,t} &= B_n && \forall n \in N \\ E_{n,t}^{shiftable,min} \le x_{n,t} &\le E_{n,t}^{shiftable,max} && \forall n \in N \\ \sum_{t=1}^{24} x_{n,t} &= 0 && \forall n \in N \end{aligned} \tag{13}$$

Where, $A_n$ is the coefficients of total load $B_n = 0$. The energy cost of each user is formulated as,

$$\mathrm{C}_n = \sum_{t=1}^{24}\Big(P_t * (E_{n,t}^{non-shiftable} + E_{n,t}^{shiftable} + x_{n,t})\Big) \tag{14}$$

*5) Case 5: Dual objective:* In this case a dual objective approach is analyzed. This function comprises the PAR of load and cost both. This approach can be proven highly effective because of the summing the two main aim of the system. To add two different quantities both components need to be normalized between 0 and 1. It can be formulated as follows,
Minimize:

$$Dual\,fn = \underbrace{\widehat{PAR}}_{Norm\,PAR} + \underbrace{\alpha}_{Weightage} * \underbrace{\widehat{f(x)}}_{Norm\,Cost} \quad \forall n \in N \tag{15}$$

$$Dual\,fn = \frac{Max\left\{\hat{E}_{n,t}^{non-shiftable} + \hat{x}_{n,t}\right\}}{Avg\left(\hat{E}_{n,t}\right)} + \alpha * \left(\hat{P}_t * (\hat{E}_{n,t}^{non-shiftable} + \hat{x}_{n,t})\right) \quad \forall n \in N \tag{16}$$

$$\begin{aligned} \text{Subject to } \; A_n * x_{n,t} = B_n \qquad \forall n \in N \\ E_{n,t}^{shiftable,min} \leq x_{n,t} \leq E_{n,t}^{shiftable,max} \qquad \forall n \in N \end{aligned} \tag{17}$$

Where $A_n$ is the coefficients of constraint, which is sum of total load and $B_n = E_{n,t}^{shiftable}$. Here $\alpha$ is defined as a constant parameter which can affect the performance of optimization process. The significance of this parameter is defined in result section. The energy cost of each user is formulated as,

$$\mathrm{C}_n = \sum_{t=1}^{24} \left(P_t * (E_{n,t}^{non-shiftable} + x_{n,t})\right) \tag{18}$$

Benefits of all different case study are shown in Table I.

TABLE I
CASE STUDY

| | |
|---|---|
| Utility Beneficial | Case 1: PAR minimization with relaxed load constraints |
| | Case 2: PAR minimization with strict load constraints |
| Consumer Beneficial | Case 3: Consumer benefits with strict upper power limit |
| | Case 4: Consumer benefits with relaxed upper power limit |
| Dual Benefits | Case 5: Dual benefits for consumer and utility |

## B. Distributed Optimization using ADMM

In this paper, the optimization of convex problem set in equations (2), (6), (9), (12) and (16) has been solved by the iterative procedure in distributed manner. The distributed optimization framework overcome the disadvantage occurred in a centralized manner. Distributed optimization offers energy user to optimize their saving in seprate manner. In this framework, the user needs not to expose their information to the utility company. Therefore, optimization is done using an alternating method of multiplier ADMM in a distributed manner [24].

*1) ADMM Method:* Alternating direction method of multipliers (ADMM) is well recognize technique to distributed convex optimization. Consider a constrained convex optimization problem for function $f(x)$ ,

$$\begin{aligned} \text{Minimize } \; f(x) \\ \text{Subject to } \; Ax = B \end{aligned} \tag{19}$$

Where $x \in R^n$, $A \in R^{m\times n}$ and $f : R^n \to R$ is convex.

By using Lagrangian the problem can be expressed as,

$$L(x, y) = f(x) + y^T(Ax - B) \tag{20}$$

Where $y$ is the Lagrange multiplier. For solving the problem using Lagrangian method the dual iterative procedure can be made as,

$$\begin{aligned} x^{k+1} = argminL(x, y^k) \\ y^{k+1} = y^k + \alpha^k(Ax^{k+1} - B) \end{aligned} \tag{21}$$

Where $\alpha^k$ is a step size.The dual method can be extended to Augmented Lagrangian methods. The augmented methods are introduced to increase the robustness of dual methods. The augmented Lagrangian of problem 19 is,

$$L_\rho(x, y) = f(x) + y^T(Ax - B) + (\rho/2)\|Ax - B\|_2^2 \tag{22}$$

Where $\rho > 0$ is penalty parameter. With association of augmented Lagrangian the optimization problem can be formed as,

$$\begin{aligned} \text{Minimize } \; f(x) + (\rho/2)\|Ax - B\|_2^2 \\ \text{Subject to } \; Ax = B \end{aligned} \tag{23}$$

The dual update can be made as,

$$\begin{aligned} x^{k+1} = argminL_\rho(x, y^k) \\ y^{k+1} = y^k + \alpha^k(Ax^{k+1} - B) \end{aligned} \tag{24}$$

The augmented Lagrangian method is called alternating direct method of multipliers [25]. Steps of ADMM algorithm is presented in stepped manner in Algo. 1.

**Algorithm 1** Steps for ADMM algorithm

**Step - 1:** Given small number $\epsilon$ , $\rho$ , $\alpha$ = 0 and arbital values $f(0)$ , $x^{(k+1)}$ and $y^{(k+1)}$
**Step - 2:** Repeat
**Step - 3:** (Agent(1)) : Solve (20), to determine $L(x, y)$
**Step - 4:** (Agent(2)) : Solve (22), to determine $L_p(x, y)$
**Step - 5:** Update multiplier $\alpha^{(k+1)}$ = $\alpha^k$ + $\rho*(Ax^{(k+1)} - B)$
**Step - 6:** Untill $||Ax^{(k+1)}$ - $B|| \leq \epsilon$, set $t = t + 1$.

*2) DR distributed algorithm:* The distributed ADMM method is applied to the DR problem stated in Section III-A . The individual user problem can be easily solved by the distributed algorithm. The problem in (16) can be extended in Lagrangian form as,

$$\begin{aligned} L_\rho(x_{n,t}, y) = \sum_{t=1}^{24} \Big( (E_{n,t} + x_{n,t})^2 + \alpha * P_t * \\ (E_{n,t}^{non-shiftable} + x_{n,t})^2 + y^T(A_n x_{n,t} - B_n) \\ + (\rho/2)\|A_n x_{n,t} - B_n\|_2^2 \Big) \qquad \forall n \in N \end{aligned} \tag{25}$$

where $\rho$ is a predefined penalty parameter. Basically ADMM cycles through the following update until its convergence is reached.

$$x_{n,t}^{k+1} = argminL_{\rho}(x_{n,t}, y^k) \tag{26}$$

$$y^{k+1} = y^k + \alpha^k(A_n x^{k+1} - B_n) \tag{27}$$

To solve the equation (26) and (27), iterative procedure is continuing upto convergence is reached. The iteration of procedure is denoted by $k$. The $x_{n,t}^{k+1}$ is update by solving convex optimization problem. The problem in (26) and (27) can also be solved in parallel. In remaining paper, this iterative procedure is referred as ADMM scheduling method.

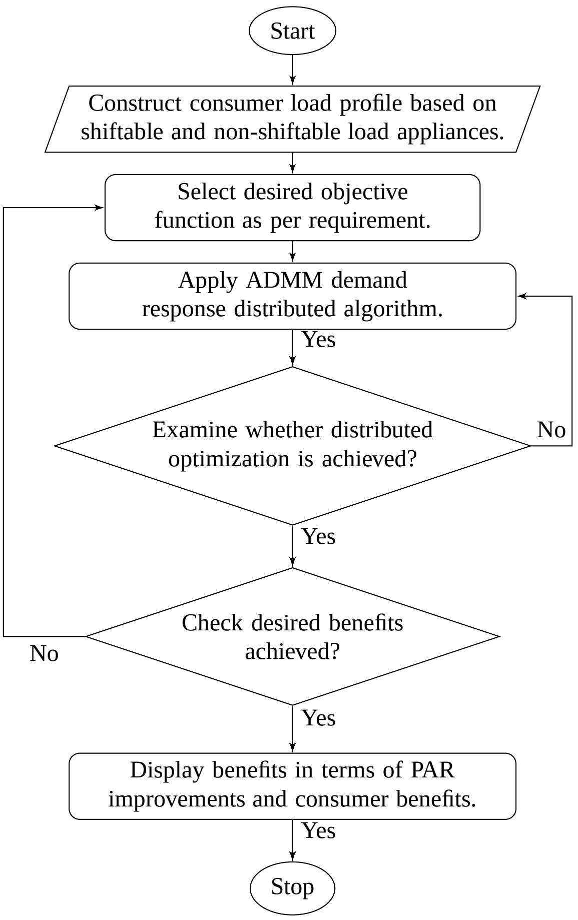


Fig. 3. Flowchart of distributed demand response framework.

Flow chart presents the demand response framework using various objective function optimized in distributed manner in Figure 3.

## IV. Numerical Results and Discussion

### A. Numerical Setup

In this paper, $N = 10$ number of residential user is considered for distributed ADMM scheduling. Each customer is considered with 15 to 20 home appliance. The appliance load of user is non-shiftable and shiftable in nature. The sum of shiftable and non-shiftable load is taken from BGE suppliers [26]. The total load of the system can be shown in Fig. 4. The customers are contracted for the RTP data information. The RTP data used in this paper has been taken from Ameren Illinois Power corporation [23]. The RTP price data is shown in Fig. 5. The implementation of proposed algorithm is executed on the platform of MATLAB software on Core i3 processor.

### B. Result and discussion

In this paper different objective approach is implemented via distributed optimization to analyze the customer saving. From the point of utility company the flatten objective load curve is highly desirable. But from the point of a customer, they focuses on their energy bill saving. Here, the customer energy bill is optimized with consideration of objective load curve. Therefore utility company and customer both will get benefits from the proposed algorithm. In the proposed distributed algorithm each user is optimizing their objectives in parallel form. The peak to average ratio for the system can be defined as,

$$\text{Peak to average ratio (PAR)} = \frac{\text{Peak load of the system}}{\text{Average load of the system}} \tag{28}$$

The Case 1 evaluates the minimization the total load on the system by load shifting technique. Here the price is not having any role in an optimization process. The unscheduled and scheduled load for case 1 is shown in Fig. 6(a). The scheduled load curve is almost flattening which shows the best possible peak to average ratio. If we see the practically the flat load curve is not easily available because of consumer preferences and lack of shiftable appliances availability. In this case, the PAR is minimized by $27.16\%$. After applying load scheduling algorithm the user has gained considerable cost saving on their bill which can be interpreted from Fig. 6(b). The total bill saving of each user is determined by the difference with and without scheduling cost. Here it can be analyzed the user which has participated in shifting with more amount of load have gained more saving on bill as compare to others. For this case, the user 2 has gained $13.93$ Cents/day, which is highest saving among all user. The total energy bill saving for the system is obtained $4.9$ %.

In the Case 2, the user is allowed to optimize only shiftable appliance load. The result in Fig. 7(a) shows the load before and after scheduling. The peak to average ratio in this case is minimized by $16$ %. The cost saving for individual user is shown in Fig. 7(b). The total cost saving for the system is maximized by $2.9$ %.

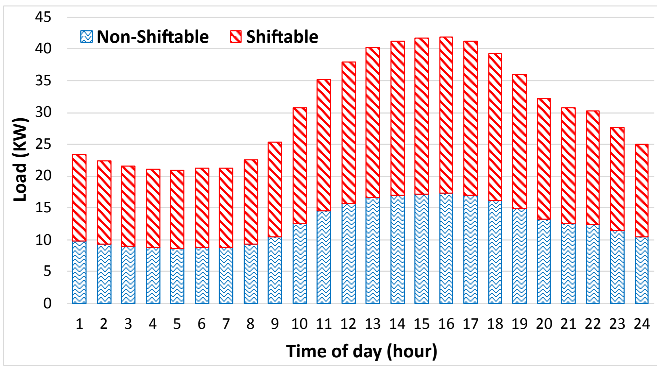


Fig. 4. Total load of the system

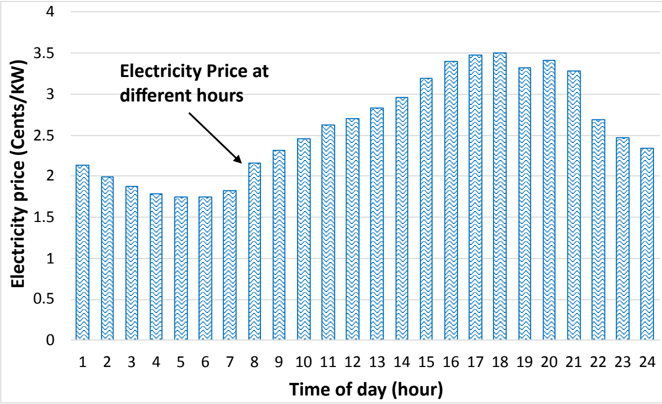


Fig. 5. RTP price data

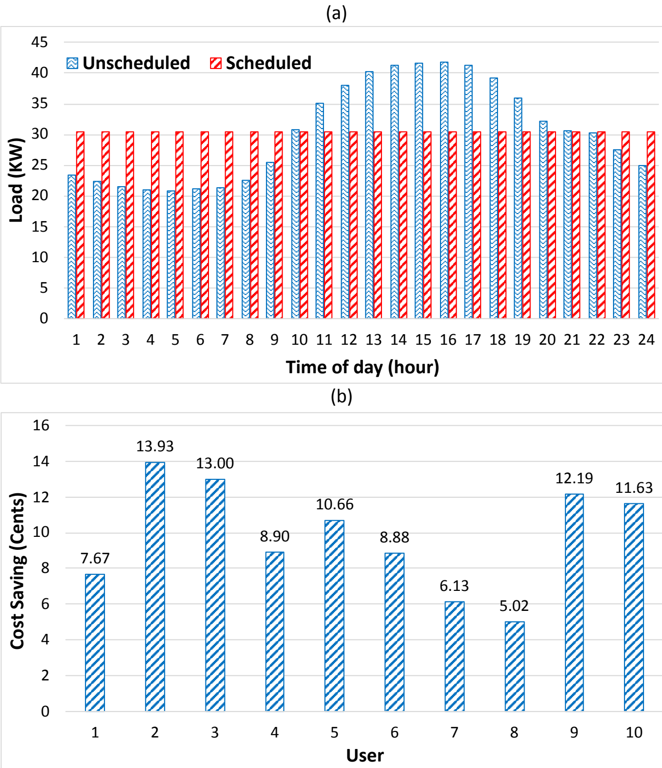


Fig. 6. Simulation results for Case 1

In the Case 3, total load minimization with RTP price coefficients is served as a goal of the optimization. The Fig. 8(a) represents the load with and without scheduling. The cost saving for each user can be represented in Fig. 8(b). In this case, the cost saving has more impact as compare to PAR. The involvement of price coefficients is proven to be efficient for cost saving purpose. The total 200.68 Cents/day cost saving is achieved for the system. Whereas individually say user 2 and user 3 has gained highest saving i.e. 25.96 and 25.17 Cents/day cost saving. The Case 4 introduces the objective as cost minimization of the individual user. The results in Fig. 9(a) shows the impact of load scheduling on the total load of the system. The proposed distributed algorithm solved each optimization problem to achieve the highest benefit for the user which lack behind the objective load curve responsibility. Therefore PAR of the system is increased for the particular case. The cost benefits redeem by an individual user can be critically examined in Fig. 9(b).

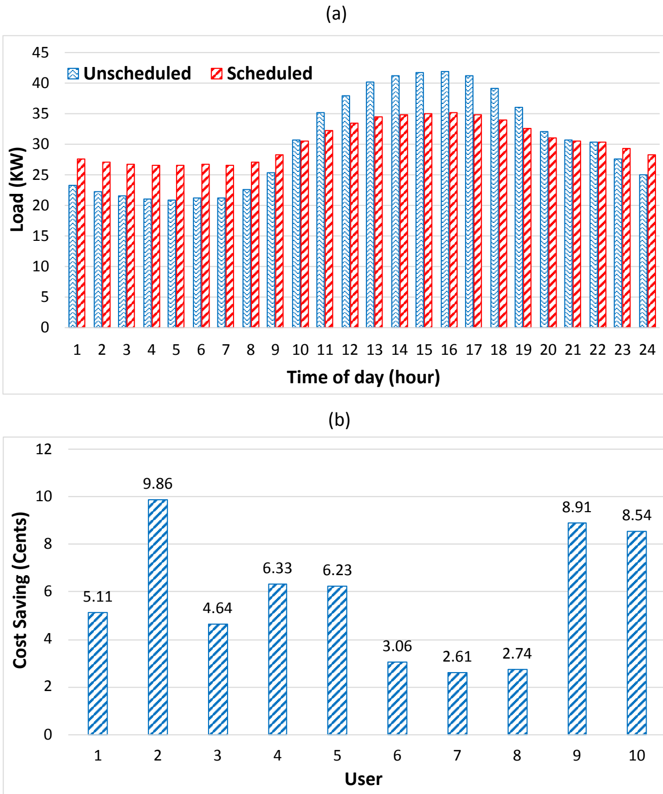


Fig. 7. Simulation results for Case 2

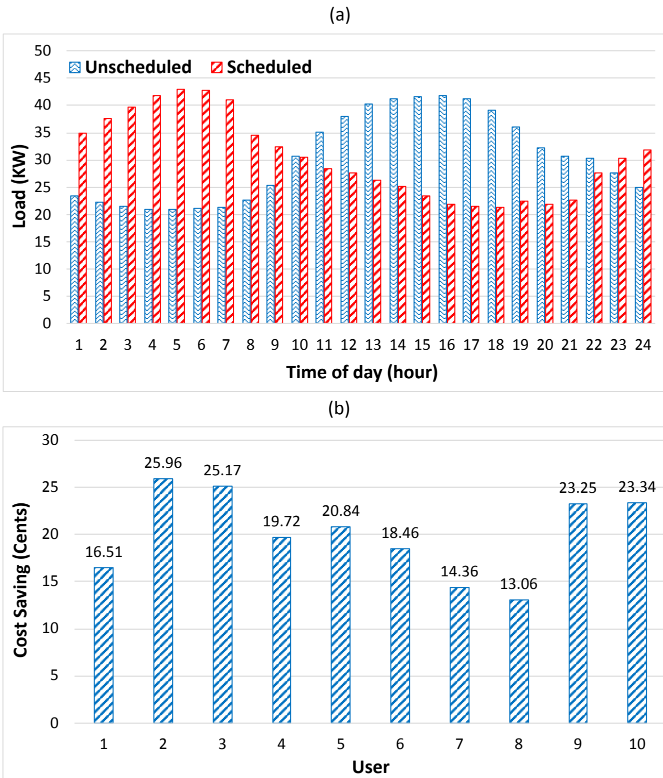


Fig. 8. Simulation results for Case 3

The total 296.4 Cents/day cost saving is obtained in this setup which is considerably large.

The Case 5 implements the optimization of function made from cost and load minimization. From the Fig. 10(a), it can be analyzed that obtained load curve is highly desirable for any utility company. The scheduled load curve almost looks

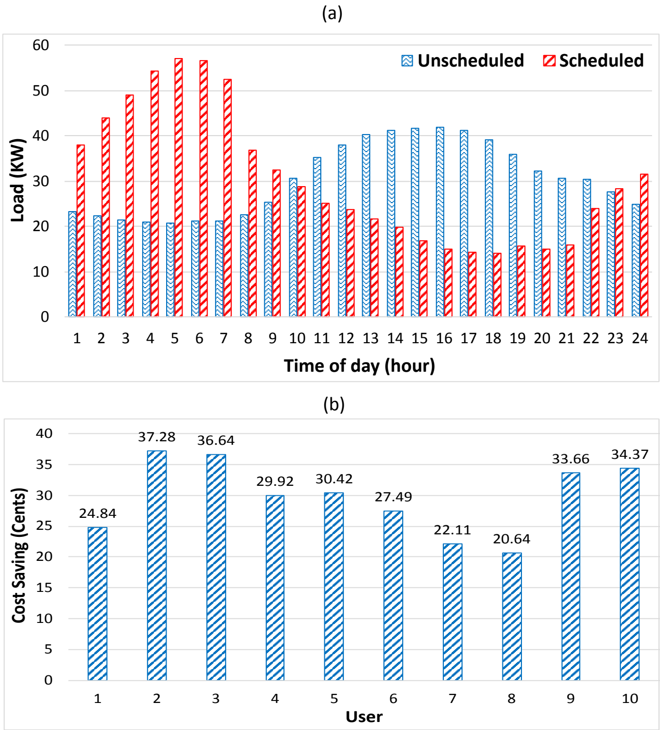


Fig. 9. Simulation results for Case 4

like flattening curve with consumer preferences. In this case both objective such as PAR minimization and cost saving both achieved in a balanced manner. The total cost saving from this case is $132.4277$ Cents/day as shown in Table II. The constant $\alpha$ represents can affect the convergence rate of algorithm, here it is considered as 0.1.

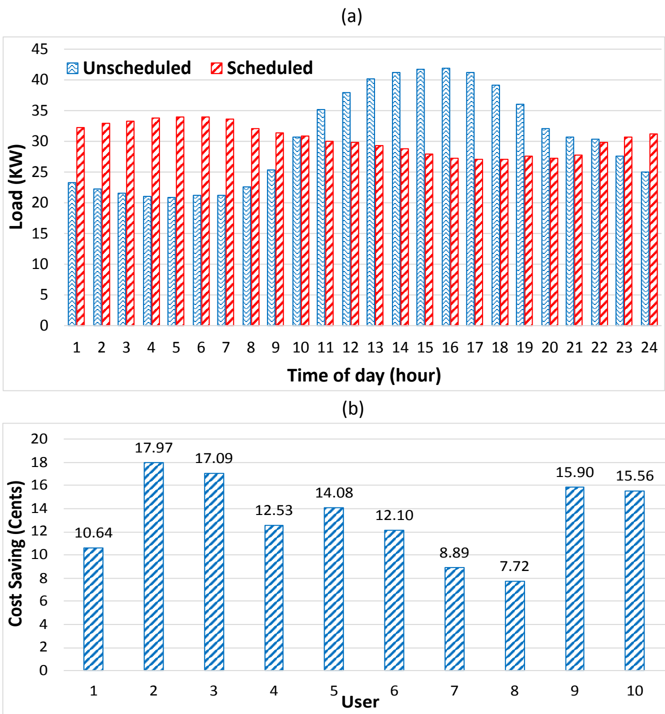


Fig. 10. Simulation results for Case 5

Fig. 11 shows the scheduled load comparison for each case with unscheduled load. From Fig. 11, it can be seen that the best load curve is achieved in Case 1 but with less amount of savings. Whereas the Case 5 offers appropriate load curve as desired for practical scenarios. For Case 5 it also gives the sufficient amount of cost saving to the users. Also from Table II, it is seen that Case 5 can be proven most suitable objective for utility as well as for user. The convergence plot for objective function of a single user is shown in Fig. 12. It can be seen that user is able to optimize their objective after completing 20 iterations of the process. The error deviation is shown in Fig. 13, which is also getting settled after 20 iterations.

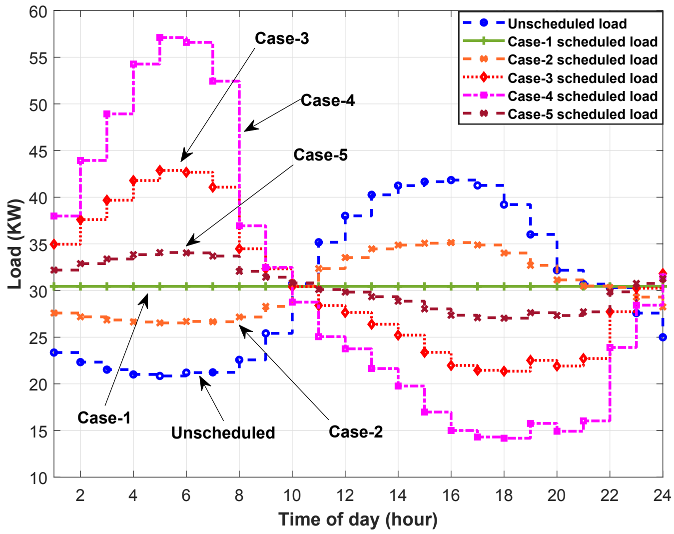


Fig. 11. Load scheduling

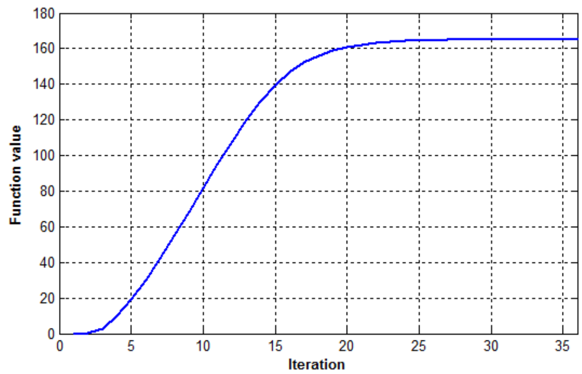


Fig. 12. Function convergence Plot

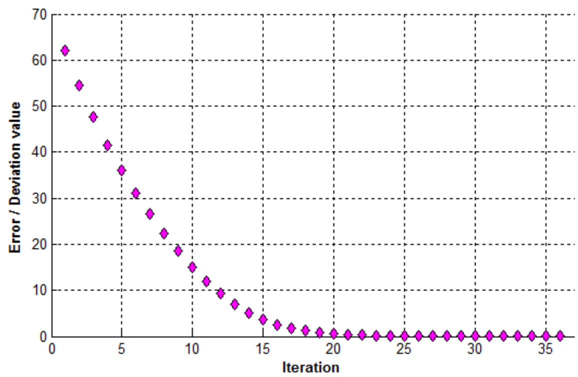


Fig. 13. Error convergence plot

As per computational aspect, it is not necessary to increase the value of $\rho$ to infinity in order to induce the convergence in method of multiplier. This is an important advantage, which results into elimination ill conditioning (non-convergence) problem. An another advantage of this method is that its convergence range is better than penalty method. The variation of penalty parameter $\rho$ has an effective impact on the algorithm. As per computational aspect, the initial value of $\rho$ should not be too large so that it will not lead to ill-condition result in first iteration. The value of parameter $\rho$ should increase with iteration so that it can utilize the positive feature of multiplier iteration. Parameter $\rho$ is not increasing fast enough to the threshold point than too much ill condition is forced upon function constraint minimization. If parameter $\rho$ increasing very slow to the threshold, it will lead to the poor convergence rate. For the algorithm the initial value $\rho_0$ has been taken 0.01. The updated value of $\rho$ with iteration has considered as $\rho = \rho_0 * 2^{iteration}$.

TABLE II
NUMERICAL RESULTS

| | Unscheduled PAR | Scheduled PAR | Total scheduled Cost (Cents) | Cost Saving (Cents) | Computation time (sec) |
|---|---|---|---|---|---|
| Case 1 | 1.3743 | 1.00 | 1894.9 | 98.0082 | 162.647 |
| Case 2 | 1.3743 | 1.1543 | 1934.9 | 58.0335 | 108.40 |
| Case 3 | 1.3743 | 1.4083 | 1792.2 | 200.6830 | 131.973 |
| Case 4 | 1.3743 | 1.8761 | 1695.6 | 296.400 | 129.312 |
| Case 5 | 1.3743 | 1.1193 | 1860.400 | 132.477 | 131.281 |

*Applicability Potential:* The proposed algorithm is applicable for wide range of application.

- Proposed algorithm is not only applicable for individual users but can also be applied on users with distribution network configuration.
- Consumer E-mobility loads can be integrated easily into the proposed algorithm.
- Parallel computation can be implement easily on proposed methodology.
- Scalability and convergence requirement can be met easily.

These key features of the proposed algorithm permits numerous application with easy modification. Thus reflects the applicability potential of the proposed algorithm.

## V. CONCLUSION

In this paper, the number of home user electricity usage models for shiftable and non-shiftable appliance loads is formed. The real-time pricing information is transferred to the user by utilizing the smart metering infrastructure. The load and cost optimization problem of the user in centralized form is converted to a distributed parallel algorithm. The optimization of an individual user is implemented in a parallel iteration procedure. The optimization problem is solved using the alternating method of multiplier in a distributed manner. A different case study is proposed to evaluate the performance of the optimization process. The results in terms of user bills and PAR have shown the effectiveness of the proposed algorithm. The specific user saving for each case study has proven the capability of the proposed algorithm. This problem can be further extended to the appliance-based study of multiple users in the smart grid framework.

## REFERENCES


[1] Q. Li, and M. Zhou, "The future-oriented grid-smart grid," *Journal of Computers*, vol. 6, no. 1, pp.98–105, 2011.

[2] Q. Qdr, "Benefits of demand response in electricity markets and recommendations for achieving them," *US Department of Energy*, 2006.

[3] P. Palensky, and D. Dietrich, "Demand side management: Demand response, intelligent energy systems, and smart loads," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 3, pp.381-388, 2011.

[4] X. Kou, F. Li, J. Dong, M. Starke, J. Munk, Y. Xue, M. Olama, and H. Zandi, "A Scalable and Distributed Algorithm for Managing Residential Demand Response Programs Using Alternating Direction Method of Multipliers (ADMM)," *IEEE Transactions on Smart Grid*, vol. 11, no. 6, pp.4871-4882, 2020.

[5] G. Abrate, "Time-of-use pricing and electricity demand response: evidence from a sample of Italian industrial customers," *International Journal of Applied Management Science*, vol. 1, no. 1, pp.21–40, 2008.

[6] R. R. Mohassel, A. Fung, F. Mohammadim, and K. Raahemifar, "A survey on advanced metering infrastructure," *International Journal of Electrical Power & Energy Systems*, vol. 63, no. 1, pp.473–484, 2014.

[7] K. Spees, and L. Lave, "Impacts of responsive load in PJM: load shifting and real time pricing," *The Energy Journal*, vol. 29, no. 2, pp.101–121, 2008.

[8] R. O. Ibrahim, E. Tambo, D. Tsuanyo, and A.N. Nguedoung, "Modelling an artificial intelligence-based energy management for household in Nigeria," *Engineering Letters*, vol. 30, no. 1, pp.140–151, 2022.

[9] Y. H. Cheng, P. J. Chao, H. Y. Liang, and C. N. Kuo, "Smart Home Environment Management Using Programmable Logic Controller," *Engineering Letters*, vol. 28, no. 4, pp.1174–1181, 2020.

[10] J. Tang, G. Tang, K. Wu, "MinNet: toward more intelligent smart home energy management systems with fewer sensors,' *International Journal of Sensor Networks*, vol. 20, no. 4, pp.252–263, 2016.

[11] R. Yu, W. Yang, and S. Rahardja, "A statistical demand-price model with its application in optimal real-time price," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp.1734–1742, 2012.

[12] A. H. Mohsenian-Rad, V. W. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Transactions on Smart Grid*, vol. 1, no. 3, pp.320–331, 2010.

[13] H. A. Aalami, M. P. Moghaddam, and G. R. Yousefi, "Evaluation of nonlinear models for time-based rates demand response programs," *International Journal of Electrical Power & Energy Systems*, vol. 65, no. 1, pp.282–290, 2015.

[14] T. Logenthiran, D. Srinivasan, and T. Z. Shun, "Demand side management in smart grid using heuristic optimization," *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp.1244–1252, 2012.

[15] X. H. Li, and S. H. Hong, "User-expected price-based demand response algorithm for a home-to-grid system," *Energy*, vol. 64, no. 1, pp.437–449, 2014.

[16] K. M. Tsui, and S. C. Chan, "Demand response optimization for smart home scheduling under real-time pricing," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp.1812-1821, 2012.

[17] C. Zhao, S. Dong, F. Li, and Y. Song, "Optimal home energy management system with mixed types of loads," *CSEE Journal of Power and Energy Systems*, vol. 1, no. 4, pp.29–37, 2015.

[18] S. B. Basapur, and B. S. Shylaja, "Constraints-relaxed functional dependency based data privacy preservation model," *Engineering Letters*, vol. 31, no. 1, pp.19–34, 2023.

[19] Z. Wang, and R. Paranjape, "Optimal residential demand response for multiple heterogeneous homes with real-time price prediction in a multi-agent framework," *IEEE Transactions on Smart Grid*, vol. 8, no. 3, pp.1173-1184, 2015.

[20] C. Gong, X. Wang, W. Xu, and A. Tajer, "Distributed real-time energy scheduling in smart grid: Stochastic model and fast optimization," *IEEE Transactions on Smart Grid*, vol. 4, no. 3, pp.1476–1489, 2013.

[21] Z. Tan, P. Yang, and A. Nehorai, "An optimal and distributed demand response strategy with electric vehicles in the smart grid," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp.861–869, 2014.

[22] Hydro BC. Residential rates, https://www.bchydro.com/accounts-billing/ratesenergy-use/electricity-rates/residential-rates.html

[23] Real-Time Pricing for Residential Customers, Ameren Illinois Power Co., Springfield, IL, USA, 2015. [Online]. Available: http://www.ameren.com/Residential/ADC˙RTP˙Res.asp

[24] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Foundations and Trends in Machine learning*, vol. 3, no. 1, pp.1-122, 2011.

[25] D. P. Bertsekas, "Constrained optimization and Lagrange multiplier methods," 2014.

[26] BGE Supplier Site Load Profiles, 2016. [Online]. Available: https://supplier.bge.com/electric/load/profiles.asp