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A Game-Theoretic Energy Scheduling Scheme with Price-Based and Incentive-Based Demand Response Programs

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Abstract: Demand response (DR) is playing a revolutionary role in changing the way demand at the distribution end is managed. In the literature, a number of centralized energy management schemes have been discussed. Due to large computational overload and privacy concerns in the centralized schemes, distributed schemes are being preferred over centralized schemes. In this paper, an energy scheduling problem (ESP) considering the impact of price-based (PB) and incentive-based (IB) DR programs is presented. The combined effect of PB and IB based DR programs with load-limiting strategy is observed on electricity cost, comfort and system load. In PB DR program, the user is charged according to a quadratic cost function whose coefficients depend on time-of-use pricing. In the IB DR program, an incentive/discount rate is applied to the consumers during peak hours. In PB and IB DR program with a peak limit, the ESP is implemented using a Nash equilibrium problem with pricing. Asynchronous Proximal Decomposition algorithm with shared constraint is implemented to obtain the optimal appliance schedule. In the end, analysis of system load profile, system cost and consumer cost in different cases is performed. The comfort of the consumers is also monitored using a discomfort index. The outcomes of the proposed scheduling scheme are compared with a mixed integer linear programming (MILP) based scheduling scheme proposed in literature. It has been observed that the proposed strategy is useful in reducing load during peak hours and minimizing the electricity bills for residential consumers.

Keywords: Demand Response, Price-Based, Incentive-Based, Nash Equillibrium, Shared Constraint

1. Introductione

There has been a huge pressure on the existing power system to fulfill the increasing demand of energy. Due to the old infrastructure and inefficiency of the power grid, it is not feasible for the existing grid to accommodate further expansions in the generation and transmission system. Demand Response (DR) has emerged as an innovative solution in dealing with the problem of increasing energy demand. DR is the transformation in the energy consumption pattern of the consumer as a result of application of an incentive or a time varying price signal [1]. DR can be applied to various energy consumption sectors viz. industrial, residential and commercial etc. According to Energy Statistics 2019 [2], residential energy consumption accounts for 24% of total energy consumption in 2017-18 in India and is likely to multiply manifold in the future due to fast electrification, increasing standard of living, and technological advancements. Various studies have estimated an increase of 5 to 6 times in residential energy consumption in India by 2030 [3]. These days, residential consumers use electric vehicle (EV), local renewable energy resources and smart home appliances whose energy can be controlled via a controller. Therefore, there is a need to develop different energy management schemes to control the energy demand of the residential sector.

The researchers in the past have studied various residential demand management schemes using different DR programs available in the market. These programs are mainly categorized into incentive-based (IB) and price-based (PB) programs [4]. Direct load control (DLC) was widely adopted in the past. The consumers enrolled in DLC program, allowed the utility to remotely control their energy-intensive appliances viz. air-conditioner and space/water heaters. This caused huge inconvenience to the consumers. The consumers gradually shifted their preference to PB DR programs. Time-of-use (TOU) pricing, critical peak pricing (CPP) and real-time pricing (RTP) are quite attractive programs in the category of PB DR programs. These pricing programs provide the users the freedom to control their appliances on their own according to the variation of electricity price during the day. PB DR programs are more popular among the consumers and the role of these programs in reshaping and controlling residential demand has been investigated

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thoroughly in [5–10]. In IB DR program, an incentive/discount is provided to the consumers for reducing their consumption during peak hours. IB program has benefits of its own but its role in residential DR needs to be explored further.

Appliances scheduling in response to incentive or PB DR program results in significant cost reduction for the residential consumer. As a result, system peak load is also reduced which benefits the utility. With the help of DR programs, the utilization of locally generated energy is also encouraged. It reduces the dependency on fossil-fuel-based energy resources and reduce the emission of greenhouse gases. DR schemes can be implemented in centralized as well as in a distributed manner, depending upon the location where the DR algorithm is executed. In the centralized approach, the utility or a central entity collects the parameters from the participating consumers and collectively solves the energy management problem (EMP) for all consumers [11–13]. However, it is difficult to collect and manage the real-time information of a large number of consumers. To solve an EMP centrally with a large number of parameters, a significant amount of computational effort and infrastructural support is required. Due to the limitations of the centralized approach, the distributed approach is being preferred [14]. In the distributed approach, EMP of each individual consumer is solved at his own premises. Then, the utility coordinates with all the consumers to arrive at an optimized value. To solve an EMP in a distributed manner, each consumer needs a home energy management system (HEMS). It houses optimization solvers to obtain the best appliance schedule for each consumer. This approach helps in securing the privacy of the consumer information.

There are various optimization techniques to obtain the solution of the EMP in a distributed way. The use of game theory in solving distributed scheme has gained a lot of attention recently. In a distributed EMP, cost model depends on the aggregated energy consumption of all the consumers. The electricity cost of a consumer is determined by energy consumption strategy of its own as well as the strategies of other consumers. Thus, a competitive scenario is evolved where each consumer tries to minimize his electricity cost. Game theory is an impressive framework in which interaction of different competitive players is modeled and studied [15]. It works well in the scenarios where two or more individuals aim at maximizing their payoffs, by taking actions suitable to them.

In this paper, a residential energy scheduling problem (ESP) is modeled using game theory and the impact of both PB and IB DR programs on the consumer's savings, comfort and total system load profile is observed. This model considers the minimization of consumer cost as the objective and the consumer comfort is maintained by scheduling the appliances according to the preferences of the consumer. We have considered that the utility has a maximum limit on the available energy. The global limit on total system profile is implemented by including a cost factor which is proportional to the constraint violation, in the objective function of the consumer. Thus, global constraints are implemented using a Nash Equilibrium Problem with Pricing (NEPP). Asynchronous Proximal Decomposition (PD) algorithm with shared constraint is utilized to attain the optimal values. The ESP is executed by considering TOU price based quadratic cost function. Later on, the impact of both TOU based cost function and IB DR program on energy demand of residential consumer is observed. In addition to PB and IB DR programs, a load limiting strategy is also implemented. Then, the results of the proposed scheme for different DR programs are analyzed. The performance of the proposed scheme is also compared with a mixed integer linear programming (MILP) based scheduling scheme proposed in [16].

The paper is organized in five sections. A schematic representation of the system and the mathematical modeling of the problem is presented in section 2. Section 3 provides a basic introduction to Nash equilibrium problems and the approach to deal with the shared constraints in Nash equilibrium problems. This section also describes the distributed algorithm to solve the ESP. The results of the optimization problem are represented in section 4. The concluding remarks regarding the application of the proposed scheme for residential consumer are presented in section 5.

A. Related Works

The research in residential DR area is mainly focused on PB DR. Various research articles [17–19] have considered cost as a function of TOU price or RTP and user aggregated energy consumption. These articles aim at optimizing the consumer's cost and achieving a flat distribution of aggregated load of all consumers. An ESP of distribution grid is proposed in [20] with the aim of minimizing the operation cost and pollution at generation side, load shedding power and deviation between renewable output power and consumer demand. In this problem, consumer loads are scheduled in response to day-ahead electricity price. The impact of RTP on the performance of a grid-connected residential complex having EV and photovoltaic system is analyzed in [21]. The functionality of energy export to the grid is also considered. A hybrid PB DR program comprised of TOU and RTP is presented in [22] to minimize the operation cost of a microgrid. The hybrid pricing scheme is shown to have better social welfare index than other pricing schemes.

There are certain applications of IB DR in energy management schemes as well. A day-ahead optimal scheduling of integrated urban energy system (IUES) considering a natural gas network and a reconfigurable electric distribution network is presented in [23]. The operation cost of IUES is minimized by controlling electricity and natural gas purchases and responsive loads participation via bilateral contracts. Load aggregator (LA) in [24] aims to determine the best incentive price to achieve desired load reduction with maximum utility to the LA and minimum loss of incentive to the users. This problem is developed using the concept of uncertainty in a Stackelberg game. In [25], the grid operator (GO) elicits DR from different sectors i.e. large industrial and small-commercial consumers using different incentives. Industrial consumers directly submit demand reduction request to GO. Service provider (SP) acts in between GO and small-commercial consumers. This is implemented using the Stackelberg game where GO's procurement cost is minimized and SP's revenue is maximized. A flexible DR pricing scheme to determine the compensation of demand resource providers in a micro-grid is presented in [26]. In this paper, an algorithm to share the benefit of micro-grid operator among demand resource providers is presented considering the IB DR program. A privacy-preserving algorithm for selecting the most promising consumer for IB DR is presented in [27]. A compensation scheme considering the inconvenience parameter, is proposed in [28] for residential consumers. These research articles consider either PB or IB DR program in the EMPs.

In [29], a bidding policy for a load agent in the day-ahead energy and the balancing market is considered. LA bidding strategy depends on RTP in day-ahead market and on incentive scheme in balancing market. An HEMS in [30] investigated the optimal cost of a user as a result of the application of PB and IB DR programs. The application of TOU, emergency DR and CPP in operating cost optimization problem of a Genco in the day-ahead and RTP market is analyzed in [31]. The impact of PB and IB DR programs for a single household is studied in [16]. The impact of different PB and IB programs on the certain parameters of plug-in EV (PEV) parking lots i.e. charging behavior of PEVs, energy exchange with grid and profit of parking lots is analyzed in [32]. A tri-objective optimal scheduling of energy hub is presented in [33] to minimize operating cost, emission pollution and load deviation between the load profiles before and after the scheduling. In this, deferrable load shifting is executed considering PB DR program whereas interruptible load bidding is used to provide energy reserve in the system. A multi-objective load scheduling problem proposed in [34] aims to minimize electricity cost of each individual considering TOU based tariff and incentive scheme. Comparison of proposed scheme with the related works is shown in Table I.

TABLE I. COMPARISON BETWEEN THIS PAPER AND RELATED WORKS IN THE LITERATURE

Reference	Participants	Objective	PB DR Program	IB DR Program	Solution methodology	Solution Approach	Storage device	Local generation
[17]	Residential consumers	Minimization of system PAR and total system cost	TOU price-based cost function	-	Non-cooperative game	Distributed	-	-
[18]	Residential consumers	Minimization of individual energy cost	TOU price-based cost function	-	Non-cooperative game	Distributed	Yes	Yes
[19]	Residential consumers	Minimize total cost of system	TOU price-based cost function	-	Non-cooperative game	Decentralized, centralized, distributed	-	Yes
[20]	Utility Grid, Responsive consumers, distributed energy resources	Minimization the operation cost and emission pollution, Loss of load expectation and deviation between renewable sources output and scheduled load	Yes	-	epsilon-constraint method	Centralized	Yes	Yes
[21]	Residential Complex	Minimize the cost of energy import minus export in residential complex	Yes	-	MILP	Decentralized	EV as storage	Yes
[22]	Consumers, Dispatchable generation, renewable resources	Maximize the profit of a microgrid considering distribution network constraints	Yes	-	Mixed integer non-linear programming problem	Centralized	-	Yes
[23]	Integrated Urban Energy system (IUES)	Minimize the operating cost of IUES	-	Yes	GA and interior point method	Centralized	-	Yes
[24]	Load aggregator and users	Minimize utility cost of aggregator to obtain optimal incentive strategy	-	Yes	Stochastic Stackelberg game	Distributed	-	-
[25]	Grid operator(GO), Industrial	GO minimizes total procurement cost	-	Yes	Stackelberg game	Distributed	-	-

	consumer, service provider							
[26]	Microgrid operator, Users	Economic benefit of flexible demand resource and the distribution of compensation among consumers	-	Yes	Iteration-Based Chance-Constrained Method	Centralized	-	Solar and Wind resources
[27]	Utility company, demand response provider and customers	Select the optimal customer for demand reduction offer	-	Yes	Adaptive context partition method and tree-based noise aggregation mechanism	Centralized	-	-
[28]	Aggregator for the residential community	Minimum compensation cost and inconvenience to user to achieve required reduction in demand	-	Yes	MILP	Centralized	-	-
[29]	Wholesale market operator (ISO), Load Agent	Maximize profit of load agent and ISO maximizes social benefits	RTP in Day Ahead market	Incentive in balancing market	Binary non-linear programming	Centralized	-	Wind power plant on supplier side
[30]	Users	Maximize net payoff of the consumer	Yes	Yes	MILP	Decentralized	Yes	-
[31]	Gencos	Minimization of operation cost of generation companies	Yes	Yes	MILP	Centralized	-	Wind power at suppliers side
[16]	Users	Minimize cost of users	Yes	Yes	MILP	Decentralized	Yes	Yes
[32]	Parking lot operator	Maximize the profit of parking lot operator by participating in energy and reserve market	Yes	Yes	B-level stochastic MILP problem	Centralized	EV acts as storage device.	-
[33]	Energy Hub System (EHS)	Minimize the operating cost and emission pollution and deviation of total demand from desired load profile	Yes	Yes	Augmented ε-constraint	Centralized	-	Yes
[34]	Residential consumers	Minimize of electricity bill, inconvenience and peak level.	Yes	Yes	Preemptive (PR) approach, Normalized Weighted-Sum (WS) approach and compromise programming	Decentralized, Centralized	-	-
This paper	Residential Users	Minimize energy consumption of users	Yes	Yes	Non-cooperative game	Distributed	-	-

2. System Description

We consider a distributed energy scheduling system with an energy provider and a large number of residential consumers. The schematic diagram depicting smart home appliances and their interaction with utility is presented in Fig. 1. In the smart grid, the communication system is crucial in achieving demand-side management. With the help of bi-directional flow of information, the consumers and the utility can coordinate with each other by sharing individual and total system load profile respectively. The utility can send signals to inform the consumers about the DR event (duration and discount rate), electricity cost coefficients and system load profile. Utility can also monitor the consumer load at any point of time [35].

A smart meter and an HEMS are installed in each consumer premises. The smart meter receives DR signal and load information shared by utility and communicates the received information to the HEMS. The HEMS is connected to different appliances in consumer premises and collects the necessary information about their operation and consumer preferences. According to the gathered information, HEMS obtains the optimal schedule of the appliances. The consumer load model and utility cost model used in this paper are presented next in this section.

A. Consumer Load model

The residential ESP is executed for a duration of 24 hours. The time slot is of 1 hour duration. Let Υ be the set of consumers and Λ be the set of time slots. Here $I \triangleq |\Upsilon|$ and $T \triangleq |\Lambda|$. Each consumer has a number of appliances which are divided into two categories: Non-Shiftable appliances (NSAs) and shiftable appliances (SAs).

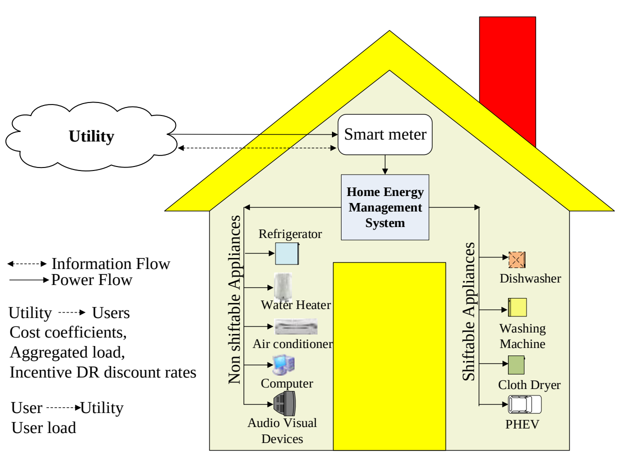

Figure 1. Representation of smart home appliances and their interaction with utility

Energy consumed by an NSA is assumed to be fixed and doesn't change with change in price or incentive. Energy demand of an SA can be shifted during the day in order to achieve cost savings in the consumer's electricity bill. Set of all home appliances, NSAs and SAs of a consumer i is represented by A_i , A_i^{fixed} and A_i^{shif} respectively.

The HEMS installed at the consumer premises collects all the information related to consumer appliances and their operational preferences. The HEMS monitors the electricity consumption pattern of NSAs and SAs of the consumer. The consumer also inputs the following information into HEMS for SAs:

- total energy requirement of each appliance in a day i.e. $E_{i,a}$ where a is the appliance index.
- maximum and minimum energy consumed by each appliance in a time slot i.e. $P_a^{\max}$ and $P_a^{\min}$.
- preferred time period of operation of appliances. The earliest time by which an appliance can start operation i.e. $ST_{i,a}$ and the maximum time by which the appliance should stop operation i.e. $ET_{i,a}$.

After collecting all the information, HEMS obtains the optimal schedule of SAs and minimizes the electricity bill of the consumer.

The energy consumed by a residential consumer is defined as

$$\mathbf{x}_i = \left[x_i^1, x_i^2, ..., x_i^T \right] \quad (1)$$

where $\mathbf{x}_i$ is an energy consumption vector of consumer i and x_i^t is the energy consumed by consumer i in time slot t . Energy consumed by consumer i during time slot t is written as the summation of energy consumed by NSAs and SAs of the consumer i .

$$x_i^t = \sum_{a \in A_i^{fixed}} x_{i,a}^t + \sum_{a \in A_i^{shif}} x_{i,a}^t \qquad \forall t \in \Lambda \quad (2)$$

where $x_{i,a}^t$ is the energy consumed by an appliance a owned by consumer i during time slot t .

The daily energy requirement of an SA is fulfilled during the specified time period of operation of the appliance. The appliance does not consume any energy outside the specified time range. This is represented by (3) and (4).

$$E_{i,a} = \sum_{t=ST_{i,a}}^{ET_{i,a}} x_{i,a}^t \quad (3)$$

$$x_{i,a}^t = 0 \qquad \forall t \in \Lambda \setminus \Lambda_{i,a} \quad (4)$$

where $\Lambda_{i,a} = \left\{ ST_{i,a}, ..., ET_{i,a} \right\}$ is the set of the preferred time period of operation of appliance a owned by consumer i . $\Lambda \setminus \Lambda_{i,a}$ represents the time period except preferred time period $\Lambda_{i,a}$.

Equation (5) ensures that the energy consumed by an appliance a of consumer i in a time slot t is within the specified limit.

$$P_a^{\min} \le x_{i,a}^t \le P_a^{\max} \tag{5}$$

Now, the total load of all the consumers L_t is written as

$$L_t = \sum_{i \in \Upsilon} \sum_{a \in A_i} x_{i,a}^t \tag{6}$$

Total energy consumption of all the consumers in a day is written as

$$\sum_{t \in \Lambda} L_t = \sum_{i \in \Upsilon} \sum_{a \in A_i} E_{i,a} \tag{7}$$

B. Utility cost model

For the consumers enrolled in a PB DR program, utility charges the consumers according to TOU based quadratic cost function as shown in (8).

$$EC_t = C(L_t) = \alpha^t \cdot (L_t)^2 + \beta^t \cdot L_t + \gamma^t \tag{8}$$

where EC_t is the aggregated energy cost of all the consumers and $C(L_t)$ is a quadratic cost function of the aggregated energy of all the consumers L_t at time slot t . Coefficients α^t , β^t and γ^t are considered to be dependent on the time of use t of electricity. Coefficients β^t and γ^t are taken as zero. This assumption doesn't affect the nature of the cost function. The electricity cost is a convex function of total load of all consumers.

In an IB DR program, consumers are asked to reduce their load from their normal consumption pattern and the consumers are paid according to the amount of load reduction. We can consider different rates for different slabs of load reduction. In this paper, we have considered a fixed rate for all the reduced load. The consumers enrolled in an IB DR program receive a discount of C_i^{IBDR} represented by (9).

$$C_i^{IBDR} = \sum_{t \in \Lambda} C_{i,t}^{IBDR} = \sum_{t \in \Lambda} IR_t \cdot E_{i,t}^{IBDR} \tag{9}$$

where IR_t is the incentive rate provided by the utility at time slot t . $E_{i,t}^{IBDR}$ is the demand reduced by consumer i during time period t .

In this paper, we also consider that the utility puts a limit on the total energy consumption of all the consumers. This is ensured by including a global constraint on the ESP.

$$\sum_{i \in \Upsilon} x_i^t \le EMax^t \tag{10}$$

where $EMax^t$ is maximum energy that can be consumed by all the consumers during time slot t .

C. Consumer Objective Function

The aim of the consumer is to minimize the daily electricity cost. Using the cost model given in (8), the expression for price of electricity is written as

$$price_t = \alpha^t \cdot L_t \tag{11}$$

Hence, electricity cost of an individual $C_{i,t}$ at time slot t is written as

$$C_{i,t} = \alpha^t \cdot L_t \cdot x_i^t \tag{12}$$

Based on expression given in (12), the daily electricity cost of a consumer enrolled in a PB DR program is represented as

$$f_i(\mathbf{x}_i) = \sum_{t \in \Lambda} \alpha^t \cdot L_t \cdot x_i^t \tag{13}$$

Considering (9) and (13), the electricity cost function of a consumer enrolled in both PB and IB DR program is expressed as

$$f_i(\mathbf{x}_i) = \sum_{t \in \Lambda} \alpha^t \cdot L_t \cdot x_i^t - \sum_{t \in \Lambda} IR_t \cdot E_{i,t}^{IBDR} \tag{14}$$

$E_{i,t}^{IBDR}$ is the load reduced during the incentive period. $E_{i,t}^{IBDR}$ at time slot t is defined as

$$E_{i,t}^{IBDR} = DL_{i,t} - \sum_{a \in A_i} x_{i,a}^t \qquad \forall t \in \Lambda \tag{15}$$

where $DL_{i,t}$ is the demand of consumer i at time slot t without considering the impact of any DR program. Using the expression for $E_{i,t}^{IBDR}$ given by (15) in (14), electricity cost of the consumer is re-written as

$$f_i(\mathbf{x}_i) = \sum_{t \in \Lambda} \alpha^t \cdot L_t \cdot x_i^t - \sum_{t \in \Lambda} IR_t \cdot \left(DL_{i,t} - \sum_{a \in A_i} x_{i,a}^t \right) \tag{16}$$

Hence, the ESP is formulated as an optimization problem with the aim of minimizing daily electricity cost of a consumer represented by (16) and considering the energy consumed by appliances $x_{i,a}^t$ as decision variable. The energy consumption variable should satisfy the constraints represented by (1) – (7). Equation (10) is included as a global constraint in the optimization problem to ensure that the system load profile remains below a specified limit.

$$\min \ f_i \tag{17}$$

$$\text{s.t. (1) - (7) and (10)}$$

This problem can be solved in a centralized manner in which utility takes a decision regarding the optimal appliance schedule of the consumers. However, the centralized approach suffers from the problem of scalability and lack of privacy. Hence, a distributed approach which is free from these shortcomings, is considered to be suitable for solving this problem. The details of distributed framework for modeling ESP is provided in the next section.

3. Distributed Framework for Energy Scheduling Problem

A distributed framework for the ESP is elaborated in this section. The objective function in the optimization problem (17) represented by (13) and (16) shows that the electricity cost of a consumer not only depends on its energy consumption strategy but also on the energy consumption strategies of other consumers. The problem involves strategic interaction among a number of self-interested consumers where each player tried to optimize its objective. Hence, game theory approach seems to be appropriate in modeling such situations.

Block diagram presenting the process flow for solution of residential ESP is shown in Fig. 2. For consumers participating in different DR programs, optimization problem subject to local and global constraints is formulated using different class of Nash game. The details of these game formulations are given in next sub-sections.

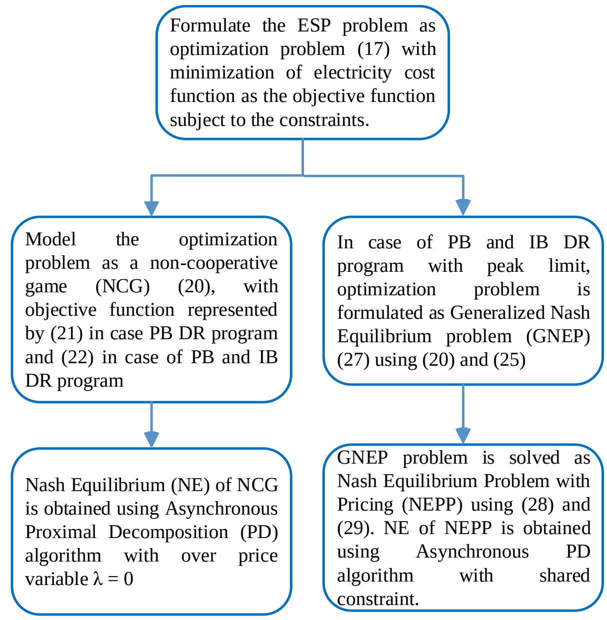

Figure 2. Process Flow diagram for solution of residential ESP

A. *Game Theoretic formulation*

Here, ESP is modeled using a non-cooperative game (NCG). Each consumer is a player who tries to minimize its daily energy consumption cost by choosing a suitable energy consumption strategy. An NCG (Γ) for ESP can be expressed in its strategic form as

$$\Gamma = \left\{ \Upsilon, (\Omega_i)_{i\in\Upsilon}, (P_i)_{i\in\Upsilon} \right\} \tag{18}$$

In (18), Υ represents the set of players/consumers, Ω_i is the strategy set of player $i \in \Upsilon$ and $\mathbf{x}_i$ is the energy consumption strategy played by player i. P_i is the payoff function of player $i \in \Upsilon$. Payoff of a player can be written as

$$\max\ P_i\left(\mathbf{x}_i, \mathbf{x}_{-i}\right) \tag{19}$$

where $\mathbf{x}_{-i}$ is the energy consumption vector of all the consumers except consumer i.

In case of PB and IB DR programs, the optimization problem (17) can be re-written as

$$\max\ P_i\left(\mathbf{x}_i, \mathbf{x}_{-i}\right) = \min\ f_i\left(\mathbf{x}_i, \mathbf{x}_{-i}\right) \tag{20}$$

$$\text{s.t. } \mathbf{x}_i \in \Omega_i$$

where Ω_i can be expressed as $\Omega_i \triangleq \left\{ \mathbf{x}_i \in R^+ : s.t.(1)-(7) \right\}$

The energy consumption function (13) of a consumer enrolled in PB DR program is re-written as

$$f_i\left(\mathbf{x}_i, \mathbf{x}_{-i}\right) = \sum_{t\in\Lambda} \alpha^t \cdot \left(x_i^t + x_{-i}^t\right) \cdot x_i^t \tag{21}$$

where x_{-i}^t is the sum of energy consumed by all the consumers except consumer i at time t.

The energy consumption function (16) of a consumer enrolled in PB and IB DR programs is written as follows:

$$f_i\left(\mathbf{x}_i, \mathbf{x}_{-i}\right) = \sum_{t\in\Lambda} \alpha^t \cdot \left(x_i^t + x_{-i}^t\right) \cdot x_i^t - \sum_{t\in\Lambda} IR_t \cdot \left(DL_{i,t} - \sum_{a\in A_i} x_{i,a}^t \right) \tag{22}$$

In both the cases, the user objectives are linked with the strategies of other users at objective function level.

B. *Global constraint handling/ Generalized Nash equillibrium problem*

The problem where one player objective and strategy both are linked with strategies of other players is called Generalized Nash equilibrium problem (GNEP). Due to the presence of a global constraint in NCG, strategy of each player also depends on the strategies of other players. Considering (10) and (20), the problem qualifies for GNEP with jointly convex shared constraint [36]. To incorporate global/shared constraint in the NCG problem, we first rewrite the expression given by (10) in the form of $G(\mathbf{x}_i,\mathbf{x}_{-i}) \le 0$ with $\mathbf{x}=\left(\mathbf{x}_i\right)_{i=1}^{I}$ as

$$\sum_{i\in\Upsilon} x_i^t - EMax^t \le 0 \quad \forall t\in\Lambda, \tag{23}$$

and

$$G(\mathbf{x}) \triangleq \left(\sum_{i\in\Upsilon} x_i^t - EMax^t\right)_{t=1}^{T} \tag{24}$$

From (24), it is observed that $G(\mathbf{x}_i,\mathbf{x}_{-i})$ is convex in $\mathbf{x}\in\Omega \triangleq \prod_{i\in\Upsilon}\Omega_i$.

The strategy set of a consumer i can be re-written as

$$\Theta_i \triangleq \left\{\mathbf{x}_i \in \Omega_i : G\left(\mathbf{x}_i,\mathbf{x}_{-i}\right) \le 0\right\} \tag{25}$$

The combined strategy set for all the consumers can be expressed as

$$\Theta \triangleq \left\{\mathbf{x} : \mathbf{x}_i \in \Omega_i \ \textit{and}\ G\left(\mathbf{x}_i,\mathbf{x}_{-i}\right) \le 0\right\} \tag{26}$$

So GNEP problem Ψ can be written as $\{\Theta, f\}$ where $f=\left(f_i\right)_{i=1}^{I}$. In GNEP, each consumer tries to minimize its cost subject to both local constraints (1)-(7) and global/shared constraint (10). GNEP problem obtained by considering (20) and (25) together can be re-written as

$$\min f_i\left(\mathbf{x}_i,\mathbf{x}_{-i}\right) \tag{27}$$

$$\text{s.t. } \mathbf{x}_i \in \Theta_i$$

The solution to the GNEP problem is usually difficult. However, the solution of GNEP problem having shared constraints can be obtained by converting the GNEP problem to NEPP [37] which is explained in the next section.

C. Nash equillibrium problem with pricing

The GNEP problem having shared constraints can be analyzed as NEPP considering $(I+1)$ players. For incorporating shared constraint, the objective function of existing I players are modified as follows:

$$\min \quad f_i\left(\mathbf{x}_i,\mathbf{x}_{-i}\right) + \lambda^{\mathrm{T}}\cdot G\left(\mathbf{x}_i,\mathbf{x}_{-i}\right) \quad \forall i\in\Upsilon \tag{28}$$

$$\text{s.t. } \mathbf{x}_i \in \Omega_i$$

where λ can be understood as the penalty imposed on the consumers if the total energy consumption of all the consumers exceed the maximum value.

The new $(I+1)^{th}$ player controls the penalty factor λ such that penalty cost charged from the players is maximized.

$$\min_{\lambda\ge 0} \quad -\lambda^{\mathrm{T}}\cdot G\left(\mathbf{x}_i,\mathbf{x}_{-i}\right) \tag{29}$$

Here $(I+1)^{th}$ player can be a central entity or utility.

D. Distributed Algorithm

A distributed algorithm to obtain the solution of the NEPP is described here. In this paper, an asynchronous PD algorithm with shared constraint [38], used for finding the Nash Equilibrium (NE) of the ESP is described in Algorithm 1. The algorithm is executed using HEMS at consumer's house.

During the process of optimization, utility shares cost coefficients α^t , incentive rates IR_t , and regularization parameter δ to the consumers on a day ahead basis. Utility also shares the aggregated load with the consumers. In this algorithm, each consumer tries to minimize its energy consumption cost over the day asynchronously considering the latest aggregated load profile available with the consumer. While minimizing the electricity cost function of a consumer, load schedule of other consumers is considered as fixed and the optimal schedule of appliances owned by the consumer is obtained. Once all the consumers obtain their optimal schedule, they share the same with the utility. The utility obtains the new value of overprice λ using the updated value of total load of all consumers according to (29). This process continues till NE for the problem is achieved. After obtaining NE, utility initiates a new iteration and updates the centroid of λ and consumers updates the centroid of $\mathbf{x}_i$. The process is repeated again and again until convergence criteria is met.

Algorithm 1: *Asynchronous PD algorithm with shared constraint*

Data: Utility shares value of cost coefficients based on TOU $(\alpha^t)_{t=1}^{T}$, incentive rates $(IR_t)_{t=1}^{T}$ and regularization parameter δ . Set iteration count $j=0$, initial value of centroids $(\bar{\mathbf{x}}_i)_{i=1}^{I}$ and $\bar{\lambda}\ge 0$. Also, assume an initial value of $\mathbf{x}$ and λ .

Step 1: Check if termination criteria is met, then STOP.

Step2: Each consumer solves its local optimization problem to find $\mathbf{x}_i^{j+1}$ such that

$$\mathbf{x}_i^{j+1} = \mathbf{x}_i^{*} \in \operatorname*{argmin}_{\mathbf{x}_i\in\Omega_i}\left\{ f_i\left(\mathbf{x}_i,\mathbf{x}_{-i}^{j}\right) + \left(\lambda^{j}\right)^{\mathrm{T}}\cdot G_i\left(\mathbf{x}_i,\mathbf{x}_{-i}^{j}\right) + \delta\cdot\left\|\mathbf{x}_i-\bar{\mathbf{x}}_i\right\|^2/2\right\} \tag{30}$$

Step 3: Utility computes the aggregated load and λ^{j+1} as

$$\lambda^{j+1} = \lambda^{*} \in \operatorname*{argmin}_{\lambda\ge 0}\left\{-\lambda^{\mathrm{T}}\cdot G(\mathbf{x}) + \delta\cdot\left\|\lambda-\bar{\lambda}\right\|^2/2\right\} \tag{31}$$

Step 4: If NE is achieved, each consumer updates its centroid values with $\mathbf{x}_i^{j+1}$ and utility updates its centroid value $\bar{\lambda}$ with λ^{j+1}.

Step 5: $j = j+1$; Go to Step 1.

Since, the algorithm allows the consumers to update their energy consumption strategies simultaneously, the algorithm is scalable for large network size. The algorithm present a linear convergence rate [18], [38]. A flowchart describing the process of optimization is presented in Fig. 3. When users participate in different DR programs, objective function of the optimization problem is modified as follows:

1) PB DR Program

$$f_i(\mathbf{x}_i,\mathbf{x}_{-i}) = \sum_{t\in\Lambda}\left[\alpha^t.\left(x_i^t + x_{-i}^t\right)\cdot x_i^t + \delta\cdot\left(x_i^t - \bar{x}_i^t\right)^2/2\right] \tag{32}$$

2) PB and IB DR Program

$$f_i(\mathbf{x}_i,\mathbf{x}_{-i}) = \sum_{t\in\Lambda}\left[\alpha^t.\left(x_i^t + x_{-i}^t\right)\cdot x_i^t - IR_t\cdot\left(DL_{i,t} - \sum_{a\in A_i} x_{i,a}^t\right) + \delta\cdot\left(x_i^t - \bar{x}_i^t\right)^2/2\right] \tag{33}$$

3) PB and IB DR Program with peak limit

$$f_i(\mathbf{x}_i,\mathbf{x}_{-i}) = \sum_{t\in\Lambda}\left[\begin{array}{l}\alpha^t.\left(x_i^t + x_{-i}^t\right)\cdot x_i^t - IR_t\cdot\left(DL_{i,t} - \sum_{a\in A_i} x_{i,a}^t\right)\\ +\left(\lambda\right)^{\mathrm{T}}\cdot\left(x_i^t + x_{-i}^t - EMax^t\right) + \delta\cdot\left(x_i^t - \bar{x}_i^t\right)^2/2\end{array}\right] \tag{34}$$

4. RESULT AND DISCUSSION

This section demonstrates the impact of consumer participation in different DR programs on consumer electricity payment, comfort and total load profile. First, the system data is presented and then the results are discussed for different cases pertaining to the problem.

A. System data

The ESP is formulated for a smart community consisting of 10 residential consumers. The time period of study is divided into 24 time slots of 1 hour each. Each consumer has a number of NSAs and SAs. Among different NSAs, each consumer possesses an air conditioner and a refrigerator which have fixed pattern of energy consumption. Rest of the NSAs are water heater, lights, audiovisual device and computer. Different consumers randomly own these NSAs. Hourly load curve of NSAs is referred from Eureco project [39]. The project monitored the energy consumption of different appliances owned by residential consumers of European communities. SAs owned by consumers include dishwasher, washing machine, cloth dryer and EV. Daily energy consumption of SAs is considered as fixed and is listed in Table II. Data for the SAs is taken from the reference paper [40]. In a realistic scenario, all the consumers don't have the appliances with same energy requirement and same preferred time of operation. Energy requirement of different appliances for multiple consumers is obtained through normal distribution around a mean value with certain standard deviation. Preferable start time and end time of operation of the appliances is also obtained using normal distribution function. In PB DR program, utility charges the consumers using the quadratic cost function. Coefficient α^t of the cost function depends on TOU price.

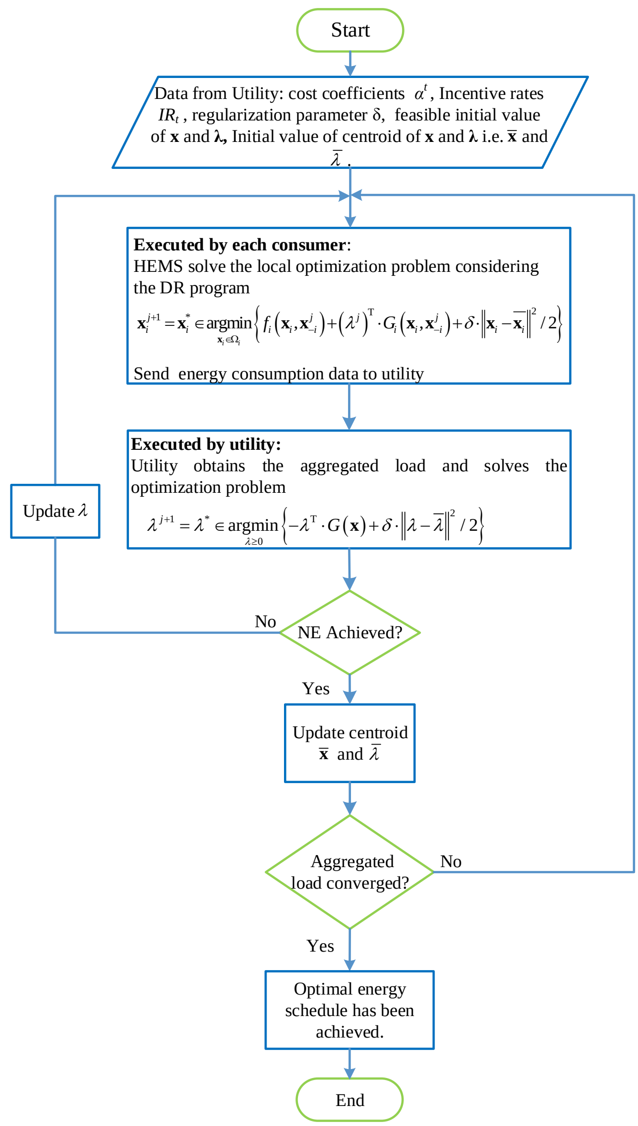

Figure 3. Flowchart depicting the optimization process

For $t = 1-17$, $\alpha^t = 0.3$ INR/kWh^2 and for $t \geq 18$, $\alpha^t = 0.6$ INR/kWh^2 (INR stands for Indian Rupee and whose present value is approx. 0.0139 US Dollar). In IB DR program, an incentive of 2.5 INR/kWh is provided by utility to the consumer for time slots $17 \le t \le 23$ and $EMax^t = 1.5 * I$ kWh where $I = 10$ residential consumers.

B. Analytical results

The results of the proposed scheme are analyzed through the following cases:

Case 1: This is the base case where appliances are operated at the beginning of the preferred time period e.g. preferred time period of operation of EV is considered from the time consumer comes back home till the time he leaves for work next morning. EVs are charged as soon as the consumer arrives home. In this case, the load profile of the consumer without the impact of any DR program is considered.

Case 2: In this case, the impact of consumer participation in PB DR Program is considered.

Case 3: In this case, the impact of consumer participation in PB and IB DR Program is observed.

Case 4: In this case, the impact of maximum limit on the system load along with case 3 is considered.

GAMS 23.4.3 (CONOPT solver) is used to implement the model and solve it. The results of the proposed scheme are compared in terms of system cost, comfort and system load profile.

1) Cost comparison

Initially the performance comparison between the proposed scheme and the MILP based scheduling scheme [16] is presented. The time-varying price signal for the MILP based scheduling scheme is selected such that the application of both the prices result in same system cost initially. Table III presents the comparison between the total system costs in both the schemes.

From the table, we can see that the proposed scheme results in significant savings in the electricity cost as compared to MILP based scheduling scheme [16] in all the cases i.e. case 2, case 3 and case 4. It has been observed that in both the schemes, system cost reduces as a result of participation in PB DR program. If the consumers are the part of both PB and IB DR programs, system cost in the proposed and MILP based scheduling scheme is reduced further. However, different trend in system cost has been observed in case 4. In MILP based scheduling scheme, system cost is increased as a result of application of peak limit whereas system cost is reduced in case of the proposed scheme. Difference is due to the fact that price at any time instant is pre-determined in [16] but the price in this paper is dependent on the time of use as well as energy consumption of the consumers at that time instant and is determined through the algorithm.

TABLE II. ENERGY CONSUMPTION OF SHIFTABLE APPLIANCE IN A DAY

S. No	Appliances	Daily Energy Consumption (kWh)
1	Dishwasher	1.8
2	EV	6.25
3	Cloth Dryer	6
4	Washing Machine	1.4

TABLE III. COMPARISON OF TOTAL SYSTEM COST IN MILP BASED SCHEDULING SCHEME [16] AND THE PROPOSED SCHEME

Case. No	MILP based scheduling scheme [16]		Proposed game-theoretic scheduling scheme	
	Total System cost	*% Saving in system cost compared to case 1*	*Total System cost*	*% Saving in system cost compared to case 1*
Case 1	1761.77	-	1761.77	-
Case 2: PB DR Program	1547.49	12.16%	1008.33	42.76%
Case 3: PB + IB DR Program	1395.49	20.79%	880.13	50.04%
Case 4: PB + IB DR Program + Peak Limit	1482.81	15.83%	879.49	50.07%

When peak limit is applied on case 3 in [16], load shifts from time slots with less price to the time slots when the price is higher. Hence, the net system cost increases. In case of proposed scheme, electricity price is higher at those instants where the system load is higher and application of peak limit causes price to reduce at those instants. The excess load at these instants shift to other instants where price is less due to less load. Hence, net system cost is reduced. In case 3, system peak load is above 15 kW limit at 15 and 16th instant (system load profile is presented later in this section). Fig. 4 shows that at 15 and 16th instant, electricity price in case 4 is less as compared to case 3 due to reduction of system load. Load shifting due to peak limit causes small increase in electricity price at 11, 12, 13 and 17th instant. The decrease in electricity cost at 15 and 16th instant is more than the increase in electricity cost at other instants. Thus the proposed scheme based on distributed game-theoretic framework provides the flexibility to reduce the system load with reduced cost to consumer.

Fig. 5 presents the cost of all consumers individually in the proposed scheme for all the cases (case 1–4). Cost of the individual consumer follows the same trend as the system cost. It is observed that the cost of each individual consumer reduces when it participates in PB DR program. Electricity cost is even lesser when consumer is enrolled

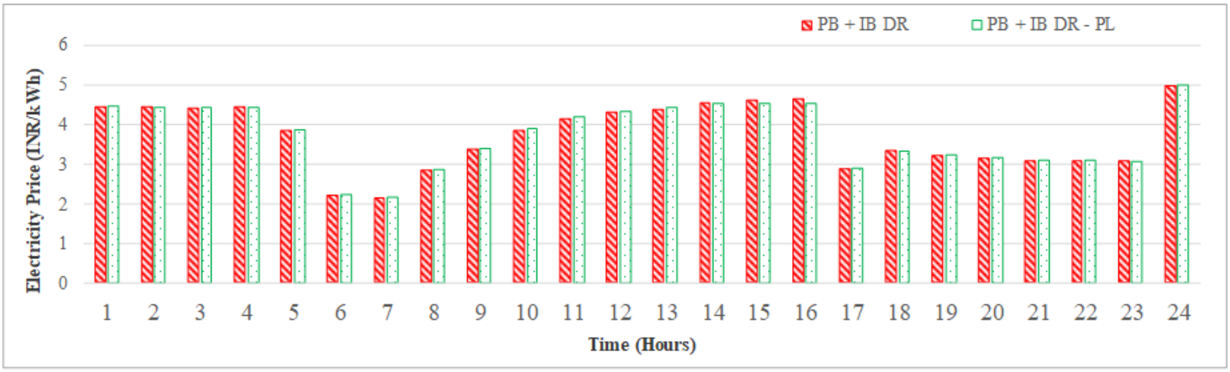

Figure 4. Comparison of electricity price in case 3 and case 4

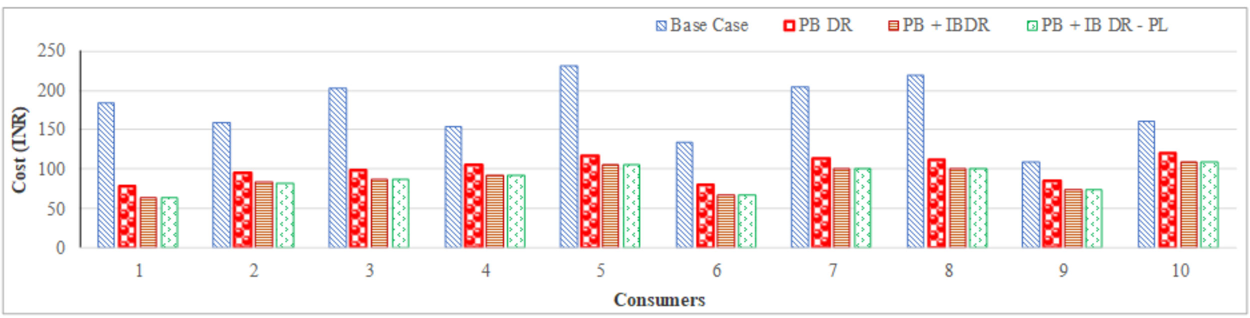

Figure 5. Comparison of individual cost for all four cases

in both PB and IB DR programs along with a peak limit on the system load.

2) Consumer comfort assessment

This section discusses the impact of DR programs on the comfort violation of the consumer. The parameter to assess the comfort violation or discomfort of the consumer is taken as

$$D_i = \sum_{t\in\Lambda} \sum_{a\in A_i^{shif}} (x_{i,a\ desired}^t - x_{i,a}^t)^2 \qquad (35)$$

where $x_{i,a\ desired}^t$ is the energy consumption of appliance a of user i at time slot t in the base case. Table IV presents the comparison of the comfort violation of the consumers in different DR programs. From the table, it has been observed that consumers discomfort is more when they participate in PB DR program as compared to the case 1 with no DR program. Consumer discomfort in case 3 is higher than the discomfort in case 2. Hence, it is interpreted that the reduction of cost in case 3 is achieved at the cost of increased discomfort to the consumers. Further, discomfort in case 4 is less as compared to case 3 but more than the discomfort in case 2. In case of distributed game theoretic framework, participation in PB and IB DR program with peak limit is beneficial to the consumers as compared to PB and IB DR program without peak limit in terms of cost and comfort. However, consumers obtain more savings at the expense of increased discomfort in PB and IB DR program with peak limit as compared with the outcomes of PB DR program.

3) System Load Profile

The system load profile in case 1 is presented in Fig. 6. The system has peaks in the morning at 10 a.m. and in the evening during 17-21 p.m. The system load profile for case 2, case 3 and case 4 have been represented in Fig. 7. It shows that as a result of the application of TOU based quadratic cost function in case 2, the peaks in system load profile are removed.

TABLE IV. INDEX OF DISCOMFORT IN THE PROPOSED SCHEME

Case. No	**Index of discomfort** (D)
Case 1	0
Case 2: PB DR Program	420.77
Case 3: PB + IB DR Program	450.60
Case 4: PB + IB DR Program + Peak Limit	449.26

During PB and IB DR program, consumers is motivated to further reduce the load during peak hours in the evening. But an increase in system load during off-peak hours has been observed. In this process, consumers received more savings in the electricity cost. In case 4, a limit on the system load is placed in addition to the application of PB and IB DR program. Thus, from the Fig. 7, it is observed that PB and IB DR program with the peak limit achieves lower value of system load during evening peak hours with a maximum load of 15 kW. Hence, we can see a combination of PB and IB DR with peak limiting property benefits the consumers in terms of cost.

5. CONCLUSION

In this paper, an ESP of residential consumers is considered. In PB and IB DR program, the problem is formulated using a non-cooperative game. A non-cooperative game with pricing is also formulated to enforce the maximum limit on the system load. An asynchronous Proximal Decomposition algorithm with shared constraint is used to obtain the optimal cost of the consumers. To emphasis the contribution of the proposed game-theoretic scheme, a comparison of the proposed scheme with a MILP based scheduling scheme is presented. Game theoretic approach presented in this paper, results in a significant reduction in consumer electricity cost as compared to the decentralized approach. Considering the proposed approach, the impact of different DR programs on the system cost, consumer cost, and their comfort and system load profile is observed. As a result of the application of TOU based quadratic cost function, the system, as well as individual cost, is minimized. System load profile is also improved. In PB and IB DR program, system cost is reduced further. Total system load reduces during peak hours and increases during the afternoon. However in this process, comfort of the user is compromised which is measured using discomfort index. In case of peak limit in PB and IB DR program, cost is improved but the comfort is reduced as compared to the case of PB DR program. It has been observed that the application of PB and IB DR with a peak limit is beneficial to the consumer in terms of cost. System load is limited within a maximum value and the load during the peak hours is reduced.

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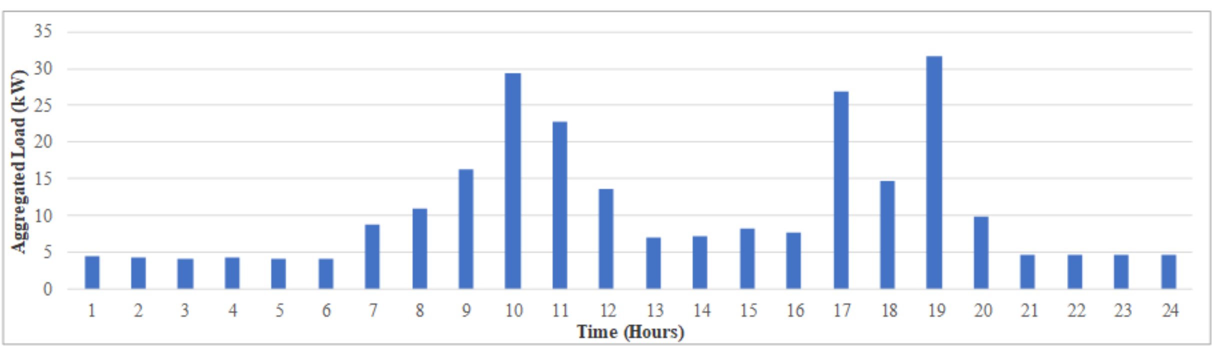

Figure 6. System load profile without considering any DR program

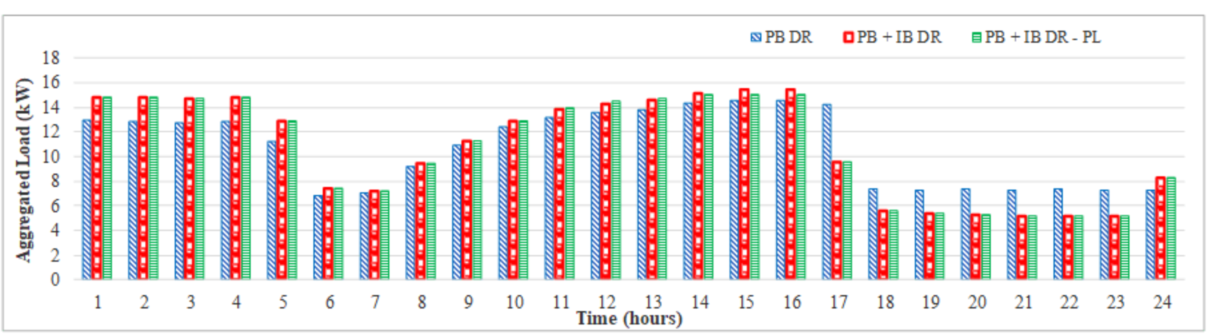

Figure 7. Comparison of system load profile in case 2, case 3 and case 4

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