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Review Article

Comparative analysis of dynamic pricing schemes in distributed energy management of residential users in smart grid

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Abstract: Increasing power demand, greenhouse gas emissions, and the old infrastructure are serious concerns in the existing power system. With the advent of the smart grid, demand response (DR) has emerged as an effective approach to handle these issues. The selection of an appropriate DR program is vital to acquire the maximum benefits for the utility and the consumers. In this context, a distributed energy management scheme for residential consumers is presented and analyzed to observe the impact of different pricing schemes. The three dynamic pricing schemes considered in this work are based on linear function, the logarithmic function, and the penalty-based linear function of aggregated load. A non-cooperative game is used to formulate the energy management problem of the consumers. The Nash equilibrium of the game is obtained using the proximal decomposition algorithm. The results are obtained for different cases based on the presence of a storage device, a dispatchable generation unit, and two different modes of operation of an electric vehicle. The best pricing scheme is chosen based on the minimum cost, the peak-to-average ratio of the system load profile, and consumer comfort.

Keywords: *Demand response, Dynamic price comparison, Energy management, Nash equilibrium, Proximal decomposition algorithm*

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Nomenclature	
DR	Demand response
EMP	Energy management problem
NAD	Non-adjustable appliances
AD	Adjustable appliance
TCA	Thermostatically controlled appliances
LPS	Linear function based Pricing Scheme
LGPS	Logarithmic function based Pricing Scheme
PLPS	Penalty based Linear Pricing Scheme
EV	Electric vehicle
EMCS	Energy management and control system
DEMS	Distributed energy management scheme
EV2G	EV to grid
PAR	Peak to average ratio
SD	Storage device
DG	Distributed generation
DGU	Dispatchable generation unit
DI	Discomfort index
TOU	Time-of-use
RTP	Real-time price

1. INTRODUCTION

Electricity demand has been expanding at an exponential rate in recent years and will continue to do so in the future. Due to the rising population and rapid economic growth, India's energy consumption has grown more than twice since 2000. It is expected to increase by 5% per year by 2040. It is mainly due to a six-fold rise in peak daily air conditioning energy use [1]. The existing power grid primarily uses fossil fuel-based generation plants to satisfy the consumers' need for electricity. However, the grid cannot withstand more expansions in the generation and transmission system due to insufficient investment. The existing power system supplies the daily peak load, which occurs only for a few hours a day. Adding more generating plants to fulfill the increasing energy demand will make the grid even more inefficient. Thus, power system flexibility is the need of the hour.

Demand Response (DR) has emerged as a novel approach to elicit flexibility from the demand-side resources. DR is the change in the consumers' energy consumption pattern from their regular consumption pattern in response to an incentive or a time-varying price signal [2]. DR enables the users to play an active role in the energy management of the system. Consumers can achieve considerable savings in their electricity bills by shifting their load demands. It also benefits the utility by reducing the peak demand of the system. Thus, it defers the need to install more generation plants and expand the transmission system. Therefore, it creates a win-win situation for both parties. Industrial, commercial, and residential sectors can all benefit from the notion of DR. In this paper, we focus on the DR scheme for residential consumers.

The use of distributed generation (DG) resources and storage devices (SD) in the distribution network and consumer households is growing. DGs help reduce the consumer's dependence on the power system. Besides, SDs play an important role in the smart grid due to their capability to reduce system losses, deal with the integration issues of renewable resources, and balance system supply and demand. The reduced cost of SDs has encouraged the adoption of these resources by the consumers [3]. These resources can enhance the DR capability of the consumers. In the current scenario, increased petrol and diesel prices encourage the users to shift to electricity-based transport mode. The market for electric vehicles (EV) has expanded significantly. Consumers prefer to charge the EVs as soon as they reach home. If EV charging is not coordinated, a large peak appears in the residential load profile in evening hours. EV also has the capability of feeding the energy back to the grid. Thus, the coordinated operation of home appliances, DGs, SDs, and EVs in the energy management problem (EMP) of the consumer needs more investigation.

There are different DR programs available in the market. They are price-based and incentive-based DR programs. In a price-based DR program, electricity price varies during the day such that the price is high at the time of peak load and low at the time of off-peak loads. These programs motivate the consumers to shift their demand based on the electricity price difference at different hours during the day. Time-of-use (TOU) price, day-ahead pricing, real-time price (RTP), critical peak price are popular price-based DR programs [4]. In an incentive-based DR program, the utility announces an incentive for the consumers to reduce their load when required. The participating consumers receive payment/penalty according to the amount of load reduced [5]. A number of research works have adopted price-based DR programs to determine consumer flexibility. The selection of a suitable DR scheme is important to achieve the highest benefits for the consumer.

The EMP can be solved in a centralized manner as well as a distributed manner. In the centralized approach, the users need to share their preferences and energy usage information with a central entity. However, the approach results in a high computational burden on the central entity, and the problem becomes intractable with a large number of consumers. It may also result in the leaking of the private data of the consumers. Therefore, a distributed approach is preferred over a centralized approach. In the distributed approach, each consumer solves its EMP such that it also maintains the system performance. For this, each consumer should be equipped with an energy management system at home.

There are different methods used in the literature to solve distributed optimization problems. These are game theory [6], alternating direction method of multipliers [7], consensus-based method, dual decomposition, and Dantzig–Wolfe decomposition [8], etc. Game theory is an excellent method for modeling and analyzing the interaction between various competitive players [9]. It works well in cases where two or more people choose to optimize their payoffs by making decisions better for them. The growing literature on game theory-based energy management schemes shows the usefulness of this technique. Dynamic pricing schemes are used in solving the EMP of the consumers in a distributed way. Electricity price in a dynamic pricing scheme depends on the time of electricity use and the aggregated energy consumption of all the consumers. The objective function, i.e., the consumer's cost function, depends on its energy consumption strategy and the energy consumption strategies of other consumers also. As a result, a competitive scenario emerges in which each consumer attempts to reduce its electricity cost.

This paper performs a comparative study of dynamic pricing schemes using a distributed energy management scheme (DEMS) for the residential consumer. Three dynamic pricing schemes, namely linear function based pricing scheme (LPS) [10], logarithmic function based pricing scheme (LGPS) [11], and penalty-based linear pricing scheme (PLPS) [12], are considered for comparison. The EMP aims to minimize consumer's cost and obtain the optimal schedule for the home appliances, SD, and dispatchable generation unit (DGU). The problem involved detailed modeling and categorization of home appliances. This study categorizes the appliances into non-adjustable (NAD), adjustable (AD), and thermostatically controlled appliances (TCA). The operation of EV is analyzed using two different modes, i.e., smart charging mode and EV2G mode. In smart charging mode, EV charging occurs at low price periods, and the electricity flows from the grid to EV. In EV2G mode, EV can also feed the power back to the home appliances or the grid. EV operates as an SD in this mode. The EMP is implemented using a non-cooperative game. Nash equilibrium of the problem is obtained using the proximal decomposition algorithm. Different case studies have been performed considering the availability of SD and DGU. The performance of DEMS using different pricing schemes is compared in terms of system cost, peak-to-average ratio (PAR) of system load, and consumers' comfort. Comparison of pricing schemes considering the strategic interaction among the consumers is the main contribution of the work.

The paper comprises seven sections. The system setup and modeling of home appliances, SD, and DGU are described in section 2. Section 3 presents the dynamic pricing schemes used in comparing the performance of DEMS. Section 4 elucidates the formulation of the game theory-based EMP of residential consumers. Section 5 presents a distributed algorithm to obtain the Nash equilibrium of the game-theoretic problem. Section 6 discusses the numerical results in detail. The conclusion is provided in Section 7.

1.1. Related Literature Works

Several DR schemes focus on coordinated energy management of different power system entities using time-varying pricing schemes. Reference [13] proposes a decentralized multi-objective optimization algorithm to schedule the energy of a residential house. The study achieves an optimal value of cost and satisfaction of the consumer considering the TOU price of electricity. A building EMP under TOU price is implemented in [14] to optimize consumer cost and comfort. A smart microgrid framework enabling energy trading among different households is presented in [15]. The energy providers use the TOU price to calculate the cost of the consumers. A multi-objective EMP of a smart distribution system is analyzed in the presence of day-ahead electricity price in [16]. An energy-sharing problem [17] considering an energy service provider and PV prosumers is studied using RTP offered by the grid. RTP scheme is extensively used in the analysis of EMP of residential consumers [18]–[20], microgrids [21], an EV charging station operator and EV owners [22], etc. An optimal sizing problem of PV and BESS in a residential household is employed considering TOU, RTP, and Stepwise electricity tariff [23].

Further, in this context, LPS is a popular dynamic price scheme widely used in distributed energy management schemes. An energy management scheme of trading the excess energy of residential consumers with community energy storage and the grid is analyzed in [24]. The grid applies a LPS to charge the consumers. A collaborative demand-side management approach [10] of residential consumers and an aggregator is modeled using a non-cooperative game. A quadratic function of aggregated load represents the system cost dynamic. A Bayesian game is modeled to analyze the bi-directional trading of household EVs in the presence of LPS [25]. LPS has also been employed to study a distributed energy storage planning scheme [26] and EMP of smart distribution system considering autonomous DR and DG [27].

There are other pricing schemes discussed in the literature. A demand-side management problem between power utility and consumers considering price based on logarithmic function is examined in [11]. A renewable facility models its electricity cost using a logarithmic function in a real-time demand-side management problem of consumer [28]. In Refs. [29] and [30], the consumer's utility function has also been represented using the logarithmic function. Another important pricing scheme is PLPS presented in the EMP discussed in [12]. A proportional and derivative (PD) pricing scheme based on the concept of PD controller has been introduced in [31], and its effectiveness in reducing the social cost of the system is evaluated. The results are compared with the proportional pricing scheme. Another novel electricity pricing scheme is proposed in [32], and its performance is observed in the demand-side management problem of residential consumers with distributed storage and generation units. The pricing scheme depends on the aggregated load and a coefficient dependent on the aggregated load. The coefficient has the same value for a range of energy but has a different (higher) value for energy exceeding the bound.

A centralized energy scheduling problem for home appliances has been evaluated and compared using TOU and RTP. [33] A hybrid-pricing program, which is a combination of RTP and TOU, has been presented in the context of a residential microgrid in [34]. The performance of the hybrid-pricing scheme is compared with RTP and TOU pricing schemes. A decentralized DR model uses a combination of RTP and incremental block rate (IBR) to achieve minimum cost and PAR value [35]. The results obtained using the combined pricing model are superior to those obtained by using only the RTP scheme. Another novel pricing scheme combining flat price, RTP, and IBR is compared with flat price, TOU, RTP, and IBR pricing scheme individually [36]. A distributed appliance scheduling problem [37] is analyzed considering TOU and LPS. Further, a game-theory-based energy management scheme [38] also presents system comparison results using TOU and LPS. Though the performance of residential energy management schemes has been compared under different pricing schemes. A comparison of a DEMS in the presence of time and load-dependent dynamic pricing schemes has not been performed. This work compares the system performance in the presence of three dynamic price schemes by executing a number of case studies. The cases are framed based on the presence of DGU, SDs, and EVs at the consumer's premises.

2. SYSTEM SETUP AND MODELING

The system considered in this study comprises a utility company and a group of residential consumers (RCs). Fig. 1 represents the system setup used in the energy management system. In this study, we assume that the total load on the system is positive. Implementing the proposed system requires an advanced metering system, a two-way communication system, and an intelligent control system to be in place. Open electricity markets and the mechanism for realizing dynamic pricing are also essential prerequisites for the implementation of DEMS. A smart meter is the first point of contact of a smart home with the utility. It records and shares the real-time energy consumption of the houses with the utility. In this scheme, a consumer needs to know the aggregated load of all the consumers and the price function coefficients. The consumer receives this information from the utility via a smart meter. All the RCs share their energy consumption information with the utility and receive the aggregated load profile from it in an iterative manner. A robust communication system is hence imperative for the system to work.

Another important component in DEMS is the energy management and control system (EMCS). It performs energy management, monitoring, and control of appliances, SD, and DGU. For this, the EMCS is connected to all the home appliances, SD and DGU, via wired connection or wirelessly. The EMCS collects information about the power requirement and the preferred operating period of the appliances. EMCS has a smart load controller that obtains the optimized schedule of home appliances, SD and DGU. Then it sends a control signal to the connected devices to perform accordingly. In addition to this, EMCS can receive consumers' commands to control their devices remotely via the internet. It also monitors the operational status and real-time energy consumption of the appliances.

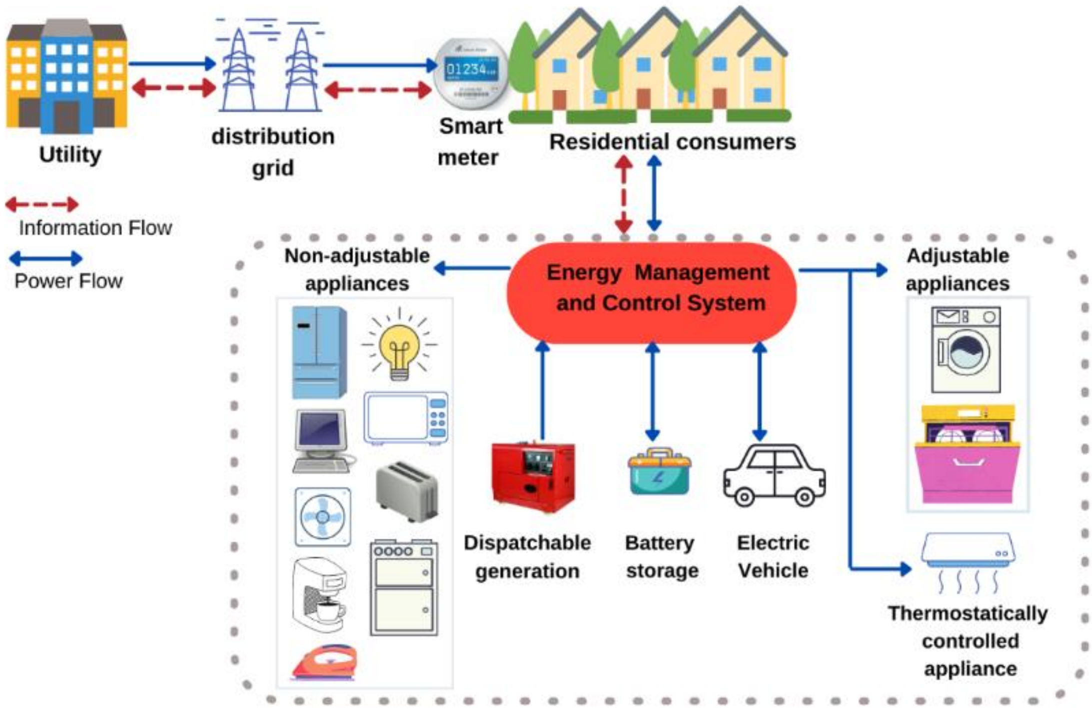


Figure 1. Illustration of the energy management system for residential consumers

2.1. Mathematical Modeling of Consumer Load

The group of RCs is represented by a set $\Upsilon = \{1,2, \ldots . I\}$ where I is the number of RCs. The time horizon of the EMP is a day divided into 24 time slots of one hour. The time slots are represented by set $\Lambda = \{1,2, \ldots \ldots, T\}$. This study categorizes the home appliances into NAD, AD, and TCA. They are characterized by set $A^{\text{NAD}}, A^{\text{AD}}$, and A^{TC}, respectively. The details of the appliances are as follows:

2.1.1. Non-adjustable appliances

These appliances have a fixed energy consumption pattern and start to consuming energy as soon as the consumer turns them on. The consumers know the energy consumption profile of these appliances in advance- for example, refrigerator, light, TV, personal computer, fan, etc.

2.1.2. Adjustable appliances

The energy consumed by these appliances can deviate from the desired energy consumption pattern. The energy consumed by the appliances can be adjusted/shifted to another time slot to minimize the daily electricity cost of the consumer. The optimal schedule of appliances is obtained by taking into account the constraints of maximum power and daily energy consumption of appliances. Examples of AD appliances are washing machine, cloth dryer, etc.

Let $\mathbf{z}_{i,a}$ be the energy consumption vector of AD appliance a of consumer i. Eq. (1) defines the vector as follows:

$$\mathbf{z}_{i,a} = \left[z_{i,a}^{1}, z_{i,a}^{2}, \dots \dots, z_{i,a}^{T}\right] \tag{1}$$

$z_{i,a}^{t}$ is the energy consumed by AD appliance a of consumer i at time slot t.

Eq. (2) represents the total energy consumption vector of all the appliances of consumer i.

$$\mathbf{zt}_{i} = [zt_{i}^{1}, zt_{i}^{2}, \dots \dots, zt_{i}^{T}] \tag{2}$$

zt_{i}^{t} is the total energy consumed by all the home appliances of consumer i at time slot t.

The optimal scheduling problem considers the following equality and inequality constraints.

Inequality constraints: The EMCS should schedule the appliances within the preferred time interval $\Lambda_{i,a}$. $\mathrm{BT}_{i,a}$, and $\mathrm{ET}_{i,a}$ is the beginning and the ending time slot of the preferred interval, respectively. The power consumption of an AD appliance during the desired period should be within a maximum and minimum value, as shown in Eq. (3).

$$z_{a}^{min} \le z_{i,a}^{t} \le z_{a}^{max} \qquad \forall t \in \Lambda_{i,a}, a \in \mathrm{A}^{\mathrm{AD}} \tag{3}$$

$z_{i,a}^{t}$ is the energy consumed by appliance a corresponding to consumer i during time interval t. z_{a}^{max} and z_{a}^{min} are the maximum and minimum power that should be consumed by the appliance a according to the appliance's specifications.

Eq. (4) ensures that the appliances do not consume energy outside the preferred interval, i.e., $\Lambda \backslash \Lambda_{i,a}$.

$$z_{i,a}^{t} = 0 \quad \forall t \in \Lambda \backslash \Lambda_{i,a}, a \in \mathrm{A}^{\mathrm{AD}} \tag{4}$$

Equality constraints: The appliance schedule should fulfill its energy requirement within the preferred time, as shown in Eq. (5).

$$\sum_{t=\mathrm{BT}_{i,a}}^{\mathrm{ET}_{i,a}} z_{i,a}^{t} = \mathrm{E}_{i,a} \quad \forall a \in \mathrm{A}^{\mathrm{AD}} \tag{5}$$

$\mathrm{E}_{i,a}$ represents the daily energy requirement of appliance a corresponding to consumer i.

2.1.3. Thermostatically controlled appliances

A TCA adjusts its energy consumption by changing the thermostat set-point. However, the thermostat set-point varies within a minimum and maximum acceptable temperature limit to ensure consumers' comfort. The air conditioner (AC) is an example of a TCA. The variation of the inside temperature of a house is expressed by Eq. (6). The inside temperature of the house at time slot t depends on the inside temperature of the house at time slot $t-1$, the outside temperature, and the power consumed by AC at time slot t [39].

$$TH_{i}^{t} = TH_{i}^{t-1} + \rho(Tout_{i}^{t} - TH_{i}^{t-1}) + \sigma PAC_{i}^{t} \quad \forall t \in \Lambda, i \in \Upsilon \tag{6}$$

TH_i^t and PAC_i^t are the inside temperature of the house and the power consumption of AC of consumer i at time slot t, respectively. $Tout_i^t$ is the outside temperature at time slot t. ρ and σ are the thermal parameters of the environment and the appliance, respectively.

The inside temperature must remain within an upper and lower temperature limit to ensure the consumer does not feel thermal discomfort. Eq. (7) presents the limits of the inside temperature.

$$TMin_i^t \leq TH_i^t \leq TMax_i^t \tag{7}$$

$$TMin_i^t = Tset_i^t - \Delta T \tag{8}$$

$$TMax_i^t = Tset_i^t + \Delta T \tag{9}$$

$TMin_i^t$ and $TMax_i^t$ are the minimum and maximum acceptable temperatures for consumer i at the time slot t inside the house. $Tset_i^t$ is the thermostat set-point of the consumer i at the time slot t. ΔT is the deviation of the upper or lower temperature limit from the thermostat set-point chosen by the consumer.

2.1.4. Electric vehicle

EV is the future of the automobile industry. Increasing demand for EVs has emphasized the need to manage their charging operation such that the utility is able to fulfill the peak demand of EVs. In this study, we assume that each consumer possesses one EV. The EV arrives home in the evening and leaves home in the morning. In a dynamic pricing scheme, EV charging is scheduled between its arrival and departure time from the house.

In this study, a consumer can choose between two modes of operation of EV. One is smart charging mode. In this mode, EV behaves like an AD appliance whose charging requirement must be satisfied by the departure time. In this mode, the EV either charges or remains idle.

EV's other mode of operation is EV2G mode. In this mode, EVs can discharge the energy to the home appliances or the grid. In this case, EV works as an SD [10]. Eqs. (10,11) express the variation of the energy stored in EV battery.

$$EEV_i^t = EEV_i^{t-1} + CP_i^t - DP_i^t \quad \forall t \in [\mathrm{AT}_i, \mathrm{DT}_i] \tag{10}$$

$$0 \leq EEV_i^t \leq EEV_i^{cap} \quad \forall t \in [\mathrm{AT}_i, \mathrm{DT}_i] \tag{11}$$

Here AT_i is the arrival time of EV at home, and DT_i is the departure time of EV from home, respectively. EEV_i^t, CP_i^t, and DP_i^t are the energy stored, charging power, and discharging power of EV owned by consumer i at time slot t, respectively. EEV_i^{cap} is the energy capacity of EV battery corresponding to consumer i. Eq. (12) represents EV battery energy level when EV returns home. The EV battery should be fully charged by the time EV leaves the house the next morning. Eq. (13) represents the battery energy constraint at the time of departure.

$$EEV_i^t = EEV_i^{ini} \quad \forall t = \mathrm{AT}_i \tag{12}$$

$$EEV_i^t = EEV_i^{cap} \quad \forall t = \mathrm{DT}_i \tag{13}$$

EEV_i^{ini} is the energy remaining in the battery of EV corresponding to consumer i at the arrival time in the house.

Charging/discharging power of EV in a time slot t varies within a maximum and a minimum limit as shown in Eqs. (14,15). In any time slot, EV can charge/discharge at a maximum rate of PEV_i^{max}.

$$0 \leq CP_i^t \leq PEV_i^{max} \quad \forall t \in [\mathrm{AT}_i, \mathrm{DT}_i] \tag{14}$$

$$0 \leq DP_i^t \leq PEV_i^{max} \quad \forall t \in [\mathrm{AT}_i, \mathrm{DT}_i] \tag{15}$$

To prevent simultaneous charge and discharge of EV, the EV model includes the following constraint.

$$CP_i^t DP_i^t = 0 \quad \forall t \in [\mathrm{AT}_i, \mathrm{DT}_i] \tag{16}$$

Eq. (17) expresses the total energy consumption of all the appliances of consumer i at time slot t.

$$zt_i^t = \sum_{a \in A^{NAD}} z_{i,a}^t + \sum_{a \in A^{AD}} z_{i,a}^t + PAC_i^t + CP_i^t - DP_i^t \qquad \forall t \in \Lambda \tag{17}$$

$\Phi_{\mathbf{zt}_i}$ is the strategy set of appliances of a consumer as represented by Eq. (18).

$$\Phi_{\mathbf{zt}_i} \triangleq \{\mathbf{zt}_i : s.t. Eqs. (3-17)\} \tag{18}$$

2.2. Storage Device and Dispatchable Generation Unit

2.2.1. Storage device

The energy stored in the SD at any time slot t can be expressed as a sum of energy stored in the previous time slot, i.e., $t-1$, and the net power consumed during the time slot t. Eq. (19) defines the variation of SD energy level with time. Stored energy should remain within a maximum and minimum value, as shown in Eq. (20).

$$QSD_i^t = QSD_i^{t-1} + CS_i^t - DS_i^t \quad \forall t \in \Lambda \tag{19}$$

$$0 \leq QSD_i^t \leq QSD_{max} \quad \forall t \in \Lambda \tag{20}$$

QSD_i^t, CS_i^t, and DS_i^t are the stored energy, charging power, and discharging power of SD corresponding to the consumer i in time slot t, respectively. QSD_{max} is the storage capacity of the SD.

The charging/discharging power of SD should be less than the maximum value presented in Eqs. (21, 22).

$$0 \leq CS_i^t \leq S_{max} \quad \forall t \in \Lambda \tag{21}$$

$$0 \leq DS_i^t \leq S_{max} \quad \forall t \in \Lambda \tag{22}$$

Eq. (23) represents a non-linear constraint to be included in the SD model to avoid simultaneous charge and discharge of SD.

$$CS_i^t DS_i^t = 0 \quad \forall t \in \Lambda \tag{23}$$

Stored energy in SD at the end of the scheduling horizon should be equal to the energy at the start of the scheduling horizon.

$$QSD_i^0 = QSD_i^{24} \tag{24}$$

Let us consider scheduling vector of SD as $\mathbf{SD}_i = ((CS_i^t)_{t=1}^T, (DS_i^t)_{t=1}^T)$. Eq. (25) defines the strategy set of an SD as

$$\Phi_{\mathbf{SD}_i} \triangleq \{\mathbf{SD}_i : s.t. Eqs. (19-24)\} \tag{25}$$

2.2.2. Dispatchable generation unit

In the literature, the authors discuss two different types of generation resources. These are non-dispatchable generation and dispatchable generation resources [40]. Non-dispatchable generation resources are the generation resources that have no operating cost and generate electricity up to their full potential- for example, solar, wind, etc. There is no strategy for energy generation by these resources.

Dispatchable generation resources are the resources with controllable energy generation. For example, internal combustion engine, biomass generator, etc. These resources have fixed cost and variable operating cost. The optimal generation strategy is determined to minimize the consumer's expenses. Eq. (26) mentions the variable cost of a DGU at time slot t as

$$\Psi_i(DG_i^t) = \eta DG_i^t \tag{26}$$

where DG_i^t is the energy generated by a DGU owned by consumer i at time slot t, and η is the DGU cost coefficient (INR/kW).

Eqs. (27,28) govern the energy generated by the DGU of a consumer i during a time slot t.

$$DG_i^t \leq DG_{max} \quad \forall t \in \Lambda \tag{27}$$

$$\sum_{t\in\Lambda} DG_i^t \leq \chi_{max} \tag{28}$$

The energy generated by DGU in a time slot should be less than a maximum value DG_{max}. χ_{max} represents the limit on the maximum energy that a DGU can generate in a day in Eq. (28). Let the DGU scheduling vector of consumer i be $\mathbf{DG}_i = \left(DG_i^t\right)_{t=1}^T$. Eq. (29) defines the strategy set for a DGU as

$$\Phi_{\mathbf{DG}_i} = \left\{\mathbf{DG}_i : \sum_{t\in\Lambda} DG_i^t \leq \chi_{max}, DG_i^t \leq DG_{max} \quad \forall t \in \Lambda\right\} \tag{29}$$

Total energy consumed by consumer i at time slot t is as follows:

$$l_i^t = zt_i^t + CS_i^t - DS_i^t - DG_i^t \qquad \forall t \in \Lambda \tag{30}$$

Let us define the aggregated load vector $\mathbf{L}$ as

$$\mathbf{L} = [L^1, L^2, \ldots., L^T] \tag{31}$$

where L^t is aggregated load of all consumers at time slot t and $L^t = \sum_{i\in\Upsilon} l_i^t$.

3. PRICING SCHEMES

The section presents the price model and cost functions used in different pricing schemes.

3.1. Linear Function Based Pricing Scheme (LPS)

In this pricing scheme, the utility adopts a quadratic cost function, as shown in Eq. (32).

$$(C_{LPS})_i^t = \alpha^t (L^t)^2 + \beta^t L^t + \gamma^t \tag{32}$$

$(C_{LPS})_i^t$ is the total electricity cost of consumers at the time slot t. Coefficients α^t, β^t and γ^t can have different values at different time slots. Eq. (33) denotes the electricity price function obtained by considering the effect of quadratic term only and taking β^t, γ^t equal to zero.

$$(EP_{LPS})^t = \alpha^t L^t \tag{33}$$

Here $(EP_{LPS})^t$ is the average price of electricity at the time slot t. It is a linear function of aggregated load.

Eq. (34) defines the cost charged from a consumer in LPS.

$$(C_{LPS})_i = \sum_{t\in\Lambda} (C_{LPS})_i^t = \sum_{t\in\Lambda} \alpha^t L^t l_i^t \tag{34}$$

3.2. Logarithmic Function Based Pricing Scheme (LGPS)

In this pricing scheme, the price function depends on the aggregated load and the logarithmic function of aggregated load as shown in Eq. (35). The average price of electricity in a time slot t is as follows:

$$(EP_{LGPS})^t = \delta^t L^t \log(1 + L^t) \tag{35}$$

The cost of a consumer in LGPS is expressed as

$$(C_{LGPS})_i = \sum_{t\in\Lambda} (C_{LGPS})_i^t = \sum_{t\in\Lambda} (EP_{LGPS})^t l_i^t \tag{36}$$

$$= \sum_{t\in\Lambda} \delta^t L^t \log(1 + L^t)\, l_i^t \tag{37}$$

3.3. Penalty-based linear pricing scheme (PLPS)

In this pricing scheme, the price function has two terms. The first term is the linear function of aggregated load (same as in LPS). The second term is a penalty/reward to the consumer if the consumer's load is above/below the average load of all the consumers. The average price function in a time slot t is as follows:

$$(EP_{PLPS})^t = \lambda^t L^t + \mu\left(L^t - L_{avg}\right) \tag{38}$$

where $L_{avg} = \sum_{t\in\Lambda} L^t / T$. λ^t is the time-varying coefficient of the price in PLPS.

The cost of a consumer in PLPS depends on the aggregated load and average load, as shown in Eq. (40).

$$(C_{PLPS})_i = \sum_{t\in\Lambda}(C_{PLPS})_i^t = \sum_{t\in\Lambda}(EP_{PLPS})^t l_i^t \tag{39}$$

$$= \sum_{t\in\Lambda}\left[\lambda^t L^t l_i^t + \mu\left(L^t - L_{avg}\right)l_i^t\right] \tag{40}$$

4. GAME-THEORETIC PROBLEM FORMULATION

The EMP of a residential consumer is an optimization problem that aims to minimize the electricity cost of the consumer. Eq. (34), Eq. (37), and Eq. (40) express the objective function of EMP in LPS, LGPS, and PLPS, respectively. The operation of appliances, SD, and DGU is subjected to different constraints. Eqs. (3-17, 19-24, 26-28, 30) outline the constraints of the optimization problem.

The input parameters that are required for obtaining the solution of EMP are

- *Maximum power, daily energy consumption, and preferred time-period of AD appliances*
- *Parameters of air conditioner model, thermostat set-point, the upper and lower limit of allowed temperature and initial value of inside temperature, air conditioner rating*
- *EV arrival and departure time, maximum charging /discharging power, EV battery energy at the time of arrival, EV capacity*
- *Initial value of stored energy in SD, maximum charging /discharging power, maximum energy storage capacity*
- *Maximum power generation per hour and total energy a DGU can generate in a day.*

EMCS executes the EMP and obtains an optimal schedule for AD appliances, EV, SD, and DGU. The decision variables of the problem are $\mathbf{zt}_i$, $\mathbf{SD}_i$, and $\mathbf{DG}_i$.

A non-cooperative game is used to solve the EMP of residential consumers in a distributed manner. The cost function of a consumer in DEMS depends not only on its own strategy set but also on the strategies adopted by other consumers.

The representation of the non-cooperative game Θ is as follows

$$\Theta = \left\{\Upsilon, \left(\Phi_{\mathbf{y}_i}\right)_{i\in\Upsilon}, (\mathrm{P}_i)_{i\in\Upsilon}\right\} \tag{41}$$

Here Υ is the set of players in the game, $\Phi_{\mathbf{y}_i}$ is the strategy set of consumer i, and P_i be the payoff of consumer i. Residential consumers are the players in this game. The strategy of a consumer involves the energy consumption strategy of all the home appliances, the energy charge and discharge strategy of the SD, and energy generated by the DGU.

The consumer's strategy vector comprising the appliance, SD, and DGU strategy vectors is indicated in Eq. (42).

$$\mathbf{y}_i = (\mathbf{zt}_i, \mathbf{SD}_i, \mathbf{DG}_i) \tag{42}$$

The strategy set $\Phi_{\mathbf{y}_i}$ of the consumer takes different values in the following cases:

1) For a consumer i having home appliances, the strategy $\Phi_{\mathbf{y}_i}$ is such that $\boldsymbol{zt}_i \in \Phi_{\boldsymbol{zt}_i}, \boldsymbol{SD}_i = 0, \boldsymbol{DG}_i = 0$

2) For a consumer i having home appliances and an SD, the strategy $\Phi_{\mathbf{y}_i}$ is such that $\boldsymbol{zt}_i \in \Phi_{\boldsymbol{zt}_i}, \boldsymbol{SD}_i \in \Phi_{\boldsymbol{SD}_i}, \boldsymbol{DG}_i = 0$

3) For a consumer i having home appliances and a DGU, the strategy $\Phi_{\mathbf{y}_i}$ is such that $\boldsymbol{zt}_i \in \Phi_{\boldsymbol{zt}_i}, \boldsymbol{SD}_i = 0, \boldsymbol{DG}_i \in \Phi_{\boldsymbol{DG}_i}$

4) For a consumer i having home appliances, an SD, and a DGU, the strategy $\Phi_{\mathbf{y}_i}$ is such that $\boldsymbol{zt}_i \in \Phi_{\boldsymbol{zt}_i}, \boldsymbol{SD}_i \in \Phi_{\boldsymbol{SD}_i}, \boldsymbol{DG}_i \in \Phi_{\boldsymbol{DG}_i}$

The payoff of the consumer in different pricing schemes is as follows:

1) In LPS, the payoff P_i is

$$\begin{aligned}\mathrm{P}_i &= -(C_{LPS})_i = -\sum_{t\in\Lambda} \alpha^t L^t l_i^t \\ &= -\sum_{t\in\Lambda} \alpha^t (l_i^t + l_{-i}^t) l_i^t\end{aligned} \tag{43}$$

2) In LGPS, the payoff P_i is

$$\begin{aligned}\mathrm{P}_i &= -(C_{LGPS})_i = -\sum_{t\in\Lambda} \delta^t L^t \log(1 + L^t)\, l_i^t \\ &= -\sum_{t\in\Lambda} \delta^t (l_i^t + l_{-i}^t) \log\big(1 + (l_i^t + l_{-i}^t)\big) l_i^t\end{aligned} \tag{44}$$

3) In PLPS, the payoff P_i is

$$\begin{aligned}\mathrm{P}_i &= -(C_{PLPS})_i = -\sum_{t\in\Lambda} \left[\lambda^t L^t l_i^t + \mu\big(L^t - L_{avg}\big) l_i^t\right] \\ &= -\sum_{t\in\Lambda} \left[\lambda^t (l_i^t + l_{-i}^t) l_i^t + \mu\big(l_i^t + l_{-i}^t - L_{avg}\big) l_i^t\right]\end{aligned} \tag{45}$$

l_{-i}^t is the total load of the system except the load of consumer i. It can be expressed as $l_{-i}^t = L^t - l_i^t$.

Each consumer will try to maximize its payoff or minimize its cost.

$$\max \mathrm{P}_i = \min f_i(\mathbf{y}_i, \mathbf{L}_{-\boldsymbol{i}}) \quad \text{s.t } \mathbf{y}_i \in \Phi_{\mathbf{y}_i} \tag{46}$$

$f_i(\mathbf{y}_i, \mathbf{L}_{-\boldsymbol{i}})$ is the cost function in different pricing schemes. $f_i(\mathbf{y}_i, \mathbf{L}_{-\boldsymbol{i}})$ is represented by $(C_{LPS})_i, (C_{LGPS})_i$, and $(C_{PLPS})_i$ in Eq. (34), Eq. (37), and Eq. (40) for LPS, LGPS, and PLPS. $\mathbf{L}_{-\boldsymbol{i}}$ is a vector that is expressed as $\left[l_{-i}^1, l_{-i}^2, \dots \dots, l_{-i}^T\right]$.

The cost function in each pricing scheme is convex, and the strategy set is compact and convex. DGU cost function is also convex. Therefore, the Nash equilibrium of the game exists and may have multiple values. For details, refer to [32]. The next section explains the distributed algorithm used to obtain a solution to the game.

5. DISTRIBUTED ALGORITHM

In DEMS, a distributed algorithm is used to obtain the solution of the non-cooperative game Θ. In this algorithm, the EMPs of all the consumers are executed in parallel. It reduces the computation time and communication requirements of the system. In this distributed algorithm, the game modifies to a regularized game as follows:

$$\max \mathrm{P}_i - \frac{\tau\left\|\mathbf{y}_i - \bar{\mathbf{y}}_i^{(k)}\right\|^2}{2} = \min f_i(\mathbf{y}_i, \mathbf{L}_{-i}) + \frac{\tau\left\|\mathbf{y}_i - \bar{\mathbf{y}}_i^{(k)}\right\|^2}{2} \tag{47}$$

The regularized game represented by Eq. (47) is solved using a distributed proximal decomposition algorithm [41]. Algorithm 1 shows a systematic process to obtain NE.

Algorithm 1: Proximal Decomposition Algorithm

Input data:

1. Parameters of AD appliances, EV, AC, SD, and DGU.
2. Load profile of NAD appliances and feasible initial load profile of consumers.
3. Aggregated load profile, pricing coefficients, and regularization parameter τ shared by the utility.
4. Centroid value $\left(\bar{\mathbf{y}}_i^{(0)}\right)_{i=1}^{I} = 0$.

S.1 Initialize outer loop count $k = 1$.

S.2 Set inner loop count $j = 1$.

S.3 for each consumer $i \in \Upsilon$, optimize

$$\mathbf{y}_i^{(k,j)} = \underset{\mathbf{y}_i \in \Phi_{\mathbf{y}_i}}{\operatorname{argmin}} \left\{ f_i\left(\mathbf{y}_i, \mathbf{L}_{-i}^{k,j-1}\right) + \frac{\tau\left\|\mathbf{y}_i - \bar{\mathbf{y}}_i^{(k-1)}\right\|^2}{2} \right\} \tag{48}$$

S.4 Share the optimized load with the utility.

S.5 At Nash equilibrium,

Consumer updates the centroid $\bar{\mathbf{y}}_i = \mathbf{y}_i^{(k)}$, and utility shares the new aggregated load.

Increment k.

Set $j = 1$

Go to S.3.

Else, Utility shares the new aggregated load.

Increment j.

Go to S.3.

S.6 If $\left\|L^{(k)} - L^{(k-1)}\right\|_2 / \left\|L^{(k)}\right\|_2 \leq \varepsilon$, STOP

Else, Utility shares the new aggregated load and Go to S.3.

The utility initially shares price coefficients, regularized parameter, and the consumers' aggregated load in this algorithm. The value of the regularization parameter should be positive and large. The algorithm executes on a day-ahead basis. In the inner loop, each consumer solves its local optimization problem Eq. (48) by keeping other consumers' load fixed. EMCS at each consumer premises obtains an optimal schedule for home appliances, SD, and DGU. The consumers share the optimal load values with utility. The utility aggregates the consumer load and communicates the updated total load with all the consumers. For each iteration of the outer loop, the inner loop executes until the Nash equilibrium is reached. Once the inner loop finishes, the utility sends a synchronization signal to update the centroid values of all consumers at the same time. The above process repeats until the aggregated load vectors between two consecutive iterations of the outer loop converge.

6. NUMERICAL RESULTS AND DISCUSSION

This section presents the optimization results to compare the benefits of different dynamic pricing schemes in DEMS. The program is executed on a personal laptop with an Intel Core i5 processor, 64-bit operating system, 8 GB RAM, and 1.8 GHz CPU. The optimization is performed using GAMS 23.4 .3 software using the CONOPT solver.

6.1. Input Data

In the optimization problem, ten residential consumers are considered. The period of the EMP is 24 hours. The appliances considered in this study are a) TCA, b) AD appliances, c) NAD appliances. Table 1 displays the energy consumption data of AD and NAD home appliances [33]. In the 'Type' column of Table 1, 'AD' and 'NAD' represents adjustable and non-adjustable appliances. The data for different consumers is obtained by randomly generating values around a mean value with a standard deviation. Each consumer has a TCA, i.e., an AC of rating 2 kW. AC's set-point is selected randomly in a range of 22-25 °C for different consumers. The maximum acceptable temperature deviation from the set-point value is 2.5 °C. The initial room temperature in each consumer's house is taken as different. The thermal parameters of the environment and the appliance ρ and σ in the AC model are taken as 0.9 and 0.008, respectively [39]. The outside temperature for a typical day in summer is presented in Fig. 2. The details of EVs involved in this study are explained in Table 2. It is assumed that energy remaining in the EV battery when EV reaches home in the evening is 30% of battery capacity. The EV needs to be charged fully at the time of departure from home. The SD considered in this study is a Li-ion battery with a capacity of 4 kWh and a charging and discharging rate of 0.5 kW. The DGU owned by the consumer is a biomass generator with a maximum capacity of 4 kWh. It can generate a maximum power of 0.4 kW in an hour. Let us assume the DGU cost coefficient $\eta = 0.039$ INR/kWh [40].

Table 1. Schedulable and Non-schedulable appliances energy data

S. No.	Appliance	Type	Power (kW)	Duration (hours)	Daily energy consumption (kWh)
1	Water pump	NAD	0.75	5-9,17-20	1.5
2	Refrigerator	NAD	0.145	1-24	3.48
3	Lights	NAD	0.16	5-10,17-24	1.92
4	Vacuum cleaner	NAD	0.74	9-12,14-17	1.48
5	Personal computer	NAD	0.1	8-18	0.4
6	Television	NAD	0.15	8-20	0.9
7	Fan	NAD	0.06	3-12, 16-22	0.9
8	Iron box	NAD	1.1	19-24	1.1
9	Coffee maker	NAD	0.35	6-8	0.35
10	Range Top	NAD	1.6	9-12	1.6
11	Microwave oven	NAD	0.8	17-20	0.8
12	Toaster	NAD	0.55	6-8	0.55
13	Toaster Oven	NAD	0.75	17-20	0.75
14	Oven	NAD	2.33	9-12	2.33
15	Oven cleaner	NAD	1.75	12-16	1.75
16	Dishwasher	AD	1.2	2-6	1.8
17	Washing machine	AD	0.4	4-8	1.4
18	Cloth dryer	AD	4	8-12	6

Table 2. The specifications of electric vehicle

Parameter	Capacity (kWh)	Charging/discharging rate (kW)
Plug-in Hybrid EV	6.25	5
Chevrolet BOLT EV	18.4	7.2
BMW 530e iPerformance Sedan	12	3.7
Hyundai IONIQ Plug-in Hybrid	8.9	4
Toyota Prius prime	8.8	1.6

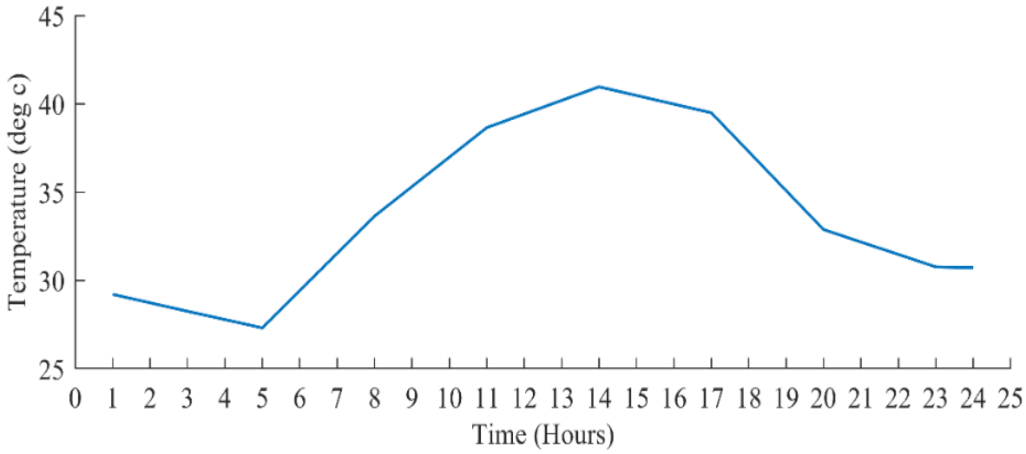


Figure 2. Outside temperature

6.2. Coefficient Determination of Pricing Scheme

To compare the system performance in the three pricing schemes, the total cost and the average price of electricity are taken as equal in all the schemes initially. For this, the coefficients of price functions are selected accordingly. The steps to obtain the coefficients of the pricing functions are explained below:

1) The hourly price of electricity is collected from the day-ahead market data from the Indian Energy exchange web portal [42]. The average price of electricity is obtained as 2.676 INR/kW. It is considered as the base price.

2) A baseline load of all the consumers is obtained. In this case, an AD appliance is assumed to operate at the onset of the preferred time interval. EV is supposed to start charging as soon as it returns home. The air-conditioner load is obtained by initially keeping the AC status off. Then, the AC thermostat is turned on and off to maintain the temperature between the upper and lower permissible limit set by the consumers.

3) In LPS, the coefficients of the pricing function are written as $\alpha^t = m(\alpha^")^t$ where m is the multiplying factor. In this pricing scheme, peak hours are considered from 9-24 hours, and off-peak hours are considered from 1-8 hours. The value of coefficients $(\alpha^")^t$ is selected such that $\alpha^"_{peak} = 1.5\alpha^"_{off-peak}$. Obtain the average price EP_{av} of electricity in this scheme using Eq. (50).

$$EP_{av} = \frac{[\sum_{t\in\Lambda}(EP_{LPS})^t L^t]}{\sum_{t\in\Lambda} L^t} \tag{49}$$

$$EP_{av} = \frac{\left[\sum_{t\in\Lambda} m(\alpha^")^t (L^t)^2\right]}{\sum_{t\in\Lambda} L^t} \tag{50}$$

The multiplying factor m is calculated using Eq. (50) such that the average price is equal to 2.676 INR/kWh. It makes the LPS equivalent to the base price, with the same value of the average price.

4) In LGPS, the coefficients of the pricing function are written as $\delta^t = m(\delta^")^t$. Here, the value of coefficients $(\delta^")^t$ is selected such that $\delta^"_{peak} = 1.5\delta^"_{off-peak}$. Eq. (51) represents the average price of electricity in LGPS.

$$EP_{av} = \frac{\left[\sum_{t\in\Lambda} m\left(\delta^{"}\right)^{t} L^{t} \log(1+L^{t}) L^{t}\right]}{\sum_{t\in\Lambda} L^{t}} \tag{51}$$

The multiplying factor m is calculated by equating the average price in Eq. (51) with 2.676 INR/kWh. The updated coefficients used in the LGPS scheme are $m\left(\delta^{"}\right)^{t}$.

5) In PLPS, the average price is obtained using Eq. (53). Coefficients $\left(\lambda^{"}\right)^{t}$ are selected such that $\lambda^{"}_{peak} = 1.5\lambda^{"}_{off-peak}$.

$$EP_{av} = \frac{\left[\sum_{t\in\Lambda} (EP_{PLPS})^{t} L^{t} + \sum_{t\in\Lambda} \mu\left(L^{t} - L_{avg}\right) L^{t}\right]}{\sum_{t\in\Lambda} L^{t}} \tag{52}$$

$$EP_{av} = \frac{\left[\sum_{t\in\Lambda} m\left(\lambda^{"}\right)^{t} (L^{t})^{2} + \sum_{t\in\Lambda} m\mu^{"}\left(L^{t} - L_{avg}\right) L^{t}\right]}{\sum_{t\in\Lambda} L^{t}} \tag{53}$$

The average price in Eq. (53) should be equal to the average value of the base price. Thus, the multiplying factor m and the updated coefficients $m\left(\lambda^{"}\right)^{t}$ and $m\mu^{"}$ are calculated.

6.3. Case study and Optimization Results

The performance of DEMS with different pricing schemes is analyzed considering EV's smart charging mode and EV2G mode. For each mode, four cases are formulated based on the resources owned by the consumer. The cases are as follows:

Case 1: In this case, consumers have NAD, AD appliances, and TCA. Consumers shift their appliances to appropriate time slots to achieve minimum cost.

Case 2: Consumers own an SD in addition to NAD, AD appliances, and TCA. SD stores the energy during off-peak hours and supplies the consumers during peak hours, bringing monetary benefits.

Case 3: Consumers own a DGU in addition to NAD, AD appliances, and TCA. DGU supplies the energy to the consumer during peak hours, thus reducing the consumers' energy demand.

Case 4: Consumers own both SD and DGU in addition to NAD, AD appliances, and TCA. The impact of both SD and DGU on the system performance is observed.

Let us first evaluate the system performance for all the cases considering smart charging mode.

6.3.1. EV with smart charging mode

Case1: EMCS at each consumer premises executes DEMS in coordination with utility. It obtains an optimal schedule for AD and TCA. Here, EV works as an AD appliance and consumes power at appropriate time slots to achieve minimum cost. Tables 3-5 show the system cost, PAR of system load profile, and discomfort index (DI) in different pricing schemes. PAR of the system load is the ratio of maximum value to the average value of the system load during the day. The discomfort index is a parameter used to indicate the discomfort of all the consumers. DI is obtained by considering the schedule of the AD appliances and AC. Discomfort to the consumer in the case of AD appliances is measured by the square of deviation of the scheduled load from baseline load. However, in AC, the consumer's discomfort is calculated by square of deviation of room temperature from the temperature set-point. Total discomfort is obtained by the addition of discomfort caused by the schedule of AD appliance and AC. It can be expressed by Eq. (54).

$$D = \sum_{i\in\Upsilon} D_i = \sum_{i\in\Upsilon}\sum_{t\in\Lambda}\left(\sum_{a\in A^{\mathrm{AD}}} \left(z_{i,aBL}^t - z_{i,a}^t\right)^2 + \left(Tset_i^T - TH_i^T\right)^2\right) \tag{54}$$

Here $z_{i,aBL}^t$ is the baseline/preferred load of appliance a of consumer i at time t.

Table 3. Comparison of system cost in different pricing schemes considering smart charging mode of EV

Case	System cost (INR)		
	LPS	LGPS	PLPS
Case 1: Home appliances	1242.85	1168.17	1242.93
Case 2: Home appliances + SD	1227.91	1148.03	1223.86
Case 3: Home appliances + DGU	1065.28	972.87	1057.45
Case 4: Home appliances + SD + DGU	1007.09	910.20	998.14

Table 4. Comparison of PAR of system load profile in different pricing schemes considering smart charging mode of EV

Case	PAR of system load profile		
	LPS	LGPS	PLPS
Case 1: Home appliances	1.719	1.718	1.718
Case 2: Home appliances + SD	1.693	1.688	1.689
Case 3: Home appliances + DGU	1.685	1.671	1.673
Case 4: Home appliances + SD + DGU	1.561	1.557	1.552

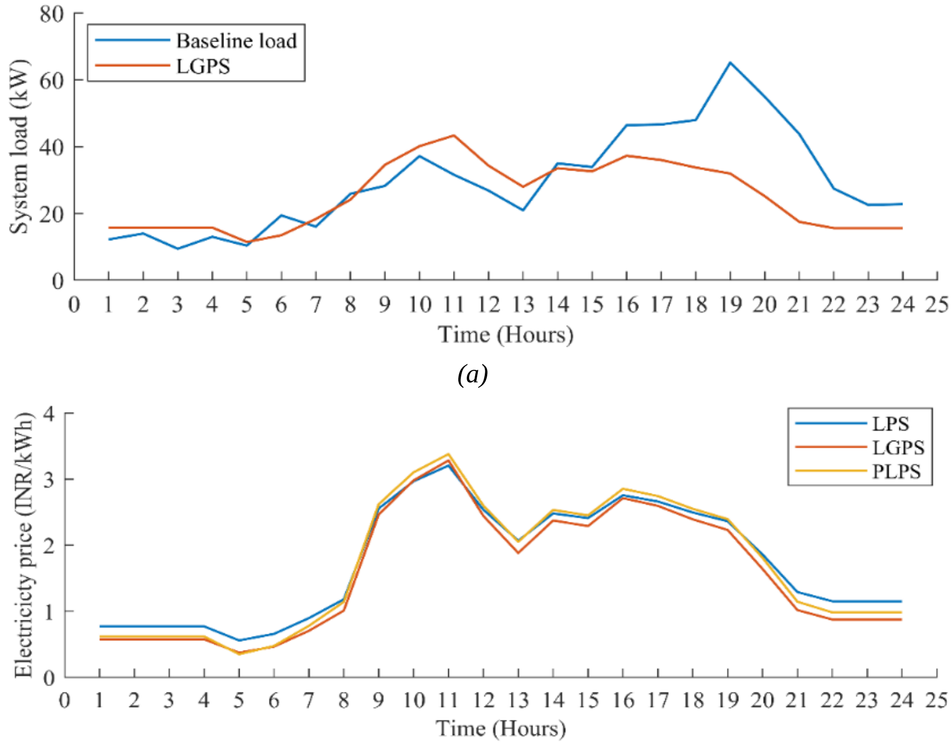
Table 5. Comparison of discomfort index in different pricing schemes considering smart charging mode of EV

Case	Discomfort Index		
	LPS	LGPS	PLPS
Case 1: Home appliances	2161.33	2161.44	2161.69
Case 2: Home appliances + SD	2161.28	2161.39	2161.63
Case 3: Home appliances + DGU	2167.30	2167.51	2168.13
Case 4: Home appliances + SD + DGU	2170.74	2169.66	2170.40

The system cost obtained after the scheduling is minimum in LGPS, as shown in Table 3. The total expenditure of the consumers is nearly the same in LPS and PLPS. Fig. 3(a) shows a comparison of the baseline load and the system load in LGPS. System load in LPS and PLPS is the same as in LGPS in case 1, so they are not shown in Fig. 3(a). Fig. 3(b) shows the hourly price of electricity attained in LPS, LGPS, and PLPS in smart charging mode. The difference in consumers' electricity costs in the three pricing schemes is due to the electricity price difference. The electricity price achieved in LGPS is less than in LPS and PLPS at all the time slots except the 11$^{\text{th}}$ time slot. Hence, the total system cost in LGPS is less than in LPS or PLPS. It can also be noticed that the price obtained in PLPS is more than in LPS during 8-21 hours and less than in LPS during 21-8 hours. In off-peak hours, system load is less than the average load, so according to Eq. (38), the electricity price in PLPS is less than LPS. In peak hours, system load is more than the average load, and hence the price is more in PLPS than in LPS during peak hours. However, the optimal system cost in LPS is almost the same as in PLPS in case 1.

Table 4 displays the PAR value of system load in the three pricing schemes considering EV's smart charging mode. In case 1, the PAR value is 1.718 in LGPS, PLPS, and 1.719 in LPS. PAR of a flat load profile is equal to one. The energy management scheme, which produces a load profile closer to one, is better. In this case, the PAR value in all the pricing schemes is almost equal.

Table 5 compares the consumers' DI in LPS, LGPS, and PLPS considering EV's smart charging mode. In case 1, the DI of the consumers is minimum when LPS is adopted. In LPS, the most comfortable appliance schedule is obtained. However, in LGPS, some comfort of the consumers is sacrificed to achieve the lowest system cost.



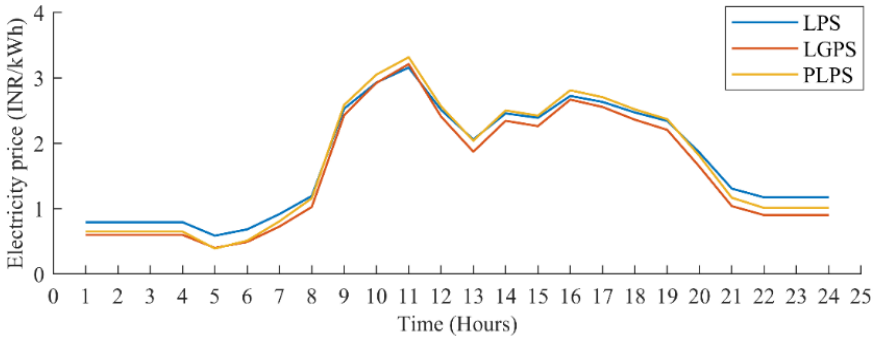
(b)

Figure 3. Hourly variation of (a) system load profile (b) electricity price in different pricing schemes in case 1 considering smart charging mode of EV

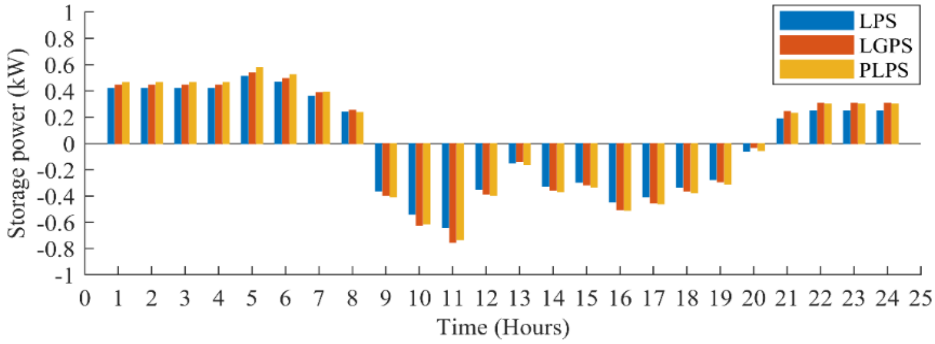
Case 2: In this case, the contribution of SD to the demand flexibility of the consumers in different pricing schemes is analyzed. EMCS executes the optimization problem at each consumer's premises to obtain the optimal schedule of home appliances and SD. Let us observe the electricity price in all the pricing schemes. Fig. 4(a) shows that the electricity price in LGPS is minimum among all pricing schemes. Hence, the system cost obtained in LGPS is the least compared to that in LPS and PLPS. The payment charged from the consumers is maximum in LPS.

Power drawn by SD in case 2 in LPS, LGPS and PLPS is shown in Fig. 4(b). A positive value means the power is charged into the SD, and a negative value means the power is discharged from the SD. It can be observed that the SD consumes power during off-peak hours and releases the power back to the home appliances during peak hours. Thus, the system load increases in off-peak hours and reduces in peak-hour. The total cost savings due to SD are calculated using electricity price and SD power values. The savings due to SD in LPS, LGPS, and PLPS are INR 7.4, 8.8, and 9.4, respectively. The benefit due to SD is more in PLPS than in LGPS. However, due to the low price in LGPS, consumers' net cost is less in LGPS than in PLPS.

Table 4 shows that in case 2, the PAR of system load has the minimum value when the consumers adopt LGPS and has the highest value in the presence of LPS. By analyzing consumers' DI in case 2 in Table 5, we follow that the minimum cost and PAR in LGPS are attained by sacrificing comfort.



(a)

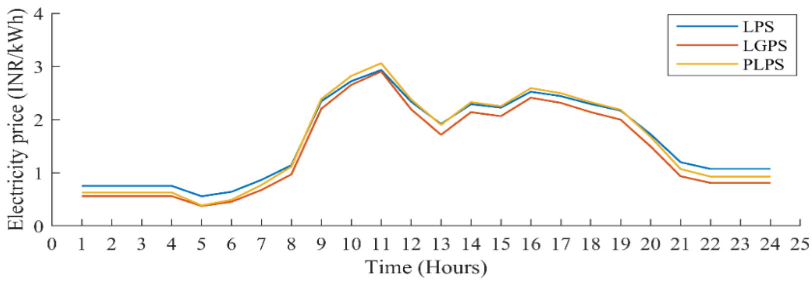


(b)

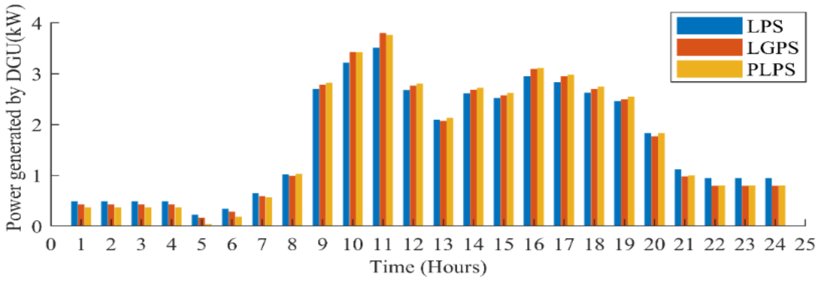
Figure 4. Plot of (a) electricity price (b) storage charging/discharging power in different pricing schemes in case 2 considering smart charging mode of EV

Case 3: The performance of DEMS for the consumers with DGU and EV following smart charging mode of operation is analyzed with the help of Fig. 5. Fig. 5(a) presents the electricity price obtained after scheduling in LPS, LGPS, and PLPS. Fig. 5(b) illustrates the total power generated by DGUs in each hour. The figure shows that DGU generates a significant portion of power during peak hours in all the pricing schemes and a small percentage of power during off-peak hours. Total energy generated by the DGU in all the pricing schemes is equal to the maximum capacity of generation of DGU. Thus, the locally generated power is utilized to the fullest. Fig. 5(c) presents the hourly benefit of all the consumers due to the energy generated by DGU. Considering the electricity price and the power generated by DGU in each hour, the hourly benefit of DGU is calculated. The total benefit of DGU in a day is obtained as INR 83.87, 79.76, and 87.13 in LPS, LGPS, and PLPS, respectively. Though the benefit of locally generated energy is maximum in PLPS, the net cost to the consumers is the minimum in LGPS than in LPS or PLPS. It is because of the lower electricity price in LGPS, as shown in Fig. 5(a).

Due to the energy generated by DGU, the total load requirement from the grid is reduced compared to case 1. As a result, electricity price and system cost are reduced as compared to case 1. Fig. 5(d) illustrates the electricity price in case 1 and case 3 when consumers follow the LGPS and smart charging mode of EV. The use of a DGU can improve the system load PAR value from 1.718 to 1.671 using LGPS. User DI calculated in LGPS is 2167.51, which is slightly higher than the minimum DI obtained in LPS, i.e., 2167.30.



(a)



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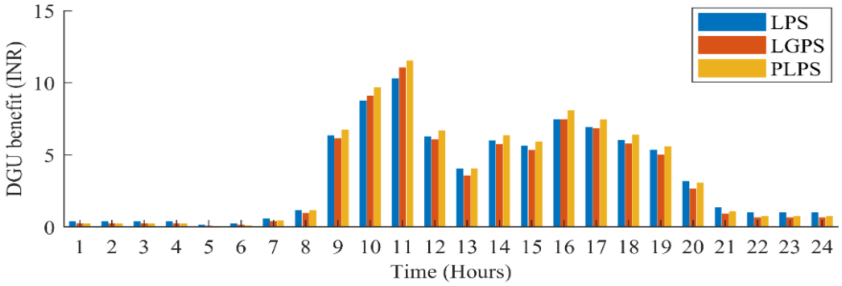
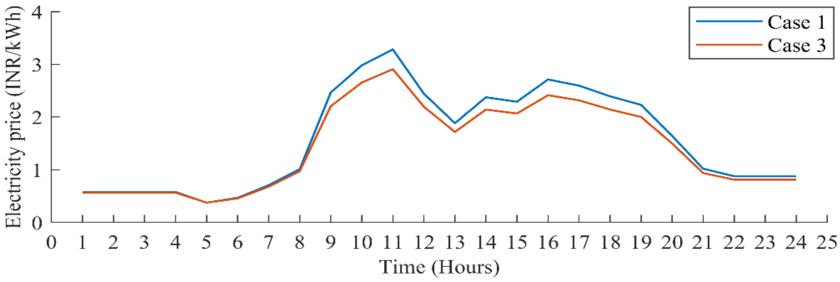


(c)



(d)

Figure 5. Hourly variation of (a) electricity price (b) power generated by DGU (c) DGU benefit to the consumers in different pricing schemes in case 3 considering smart charging mode of EV (d) comparison of electricity price in case 1 and case 3 in LGPS considering smart charging mode of EV

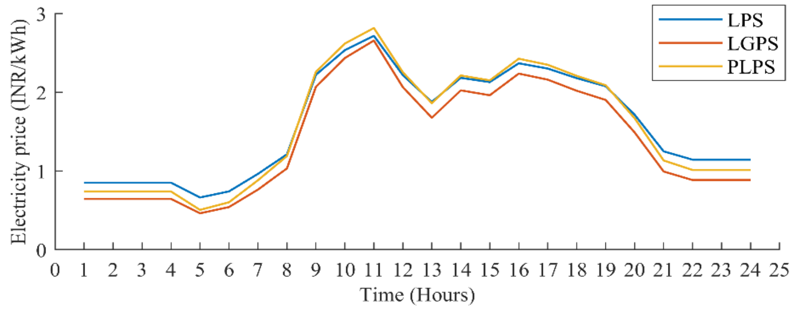
Case 4: In this case, the impact of the addition of SD and DGU is observed on system cost, PAR, and DI of the consumers. It is evident from Table 3 that the use of an SD and a DGU brings significant savings in the electricity bill of a consumer compared to the consumer without SD or DGU. The total system cost of consumers with SD and DGU is INR 1007.09, 910.20, and 998.14 in LPS, LGPS, and PLPS. The minimum system cost in case 4 is achieved in the LGPS. It is due to the lowest electricity price in LGPS at every hour among all the pricing schemes. Therefore, it is beneficial for consumers to adopt LGPS.

Figs. 6(a,b) present the electricity price and storage power in the three pricing schemes. Total cost savings due to SD is calculated as already explained in case 2. SD daily benefits in LPS, LGPS, and PLPS schemes are INR 20.7, 21.6, and 22.9, respectively. Hence, savings are more in PLPS than in LGPS. However, due to lower electricity price, the net cost of consumers is less in LGPS.

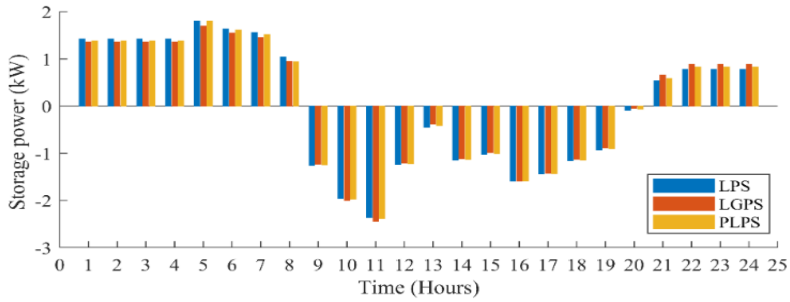
Fig. 6(c) shows the aggregated power generated by DGUs of all consumers for each hour in a day. The hourly benefit of DGU is calculated as explained previously in case 2. It has been observed that the decrement in electricity cost due to local power generation is maximum in PLPS. However, due to the minimum electricity price in LGPS, the cost of buying the net amount of power is minimum in this pricing scheme.

A comparison of the storage power in case 2 and case 4 in LGPS is displayed in Fig. 7(a). The figure presents that more power is charged into/discharged from SD in case 4. Thus, SD is better utilized in case 4. The comparison of power generated by DGU in case 3 and case 4 in LGPS is shown in Fig. 7(b).

It can be noticed from the figure that the DGU generates more power during the peak hours in case 4 than in case 3. This behavior improves the consumers' cost savings with SD and DGU compared to consumers with only SD or DGU. In this case, consumer discomfort achieved by the optimal appliance schedule is minimum in LGPS. PAR of system load in LGPS is 1.557, which is slightly higher than PAR achieved in PLPS. It shows that the cost, comfort, and PAR work in a complementary manner.



(a)



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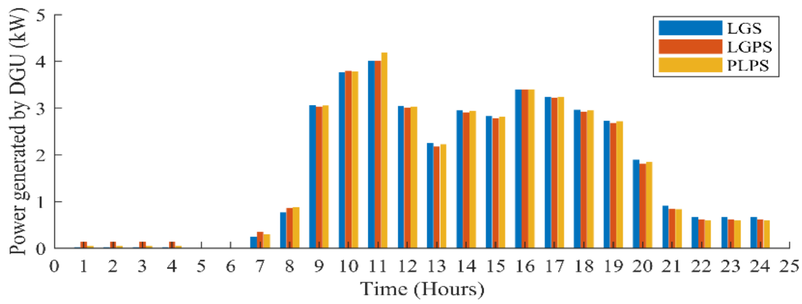
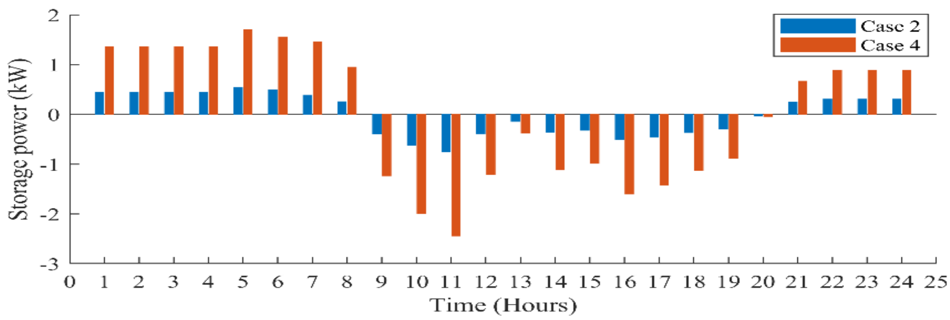


(c)

Figure 6. Plot of (a) electricity price (b) storage charging/discharging power (c) power generated by DGU in different pricing schemes in case 4 considering smart charging mode of EV



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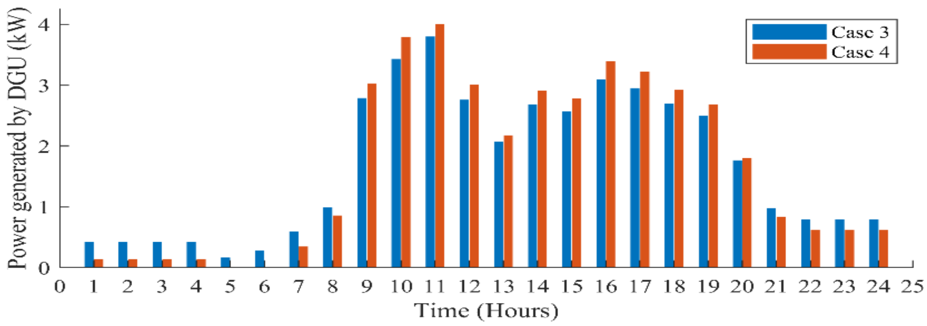


(b)

Figure 7. (a) Comparison of storage charging/discharging power in case 2 and case 4 in LGPS considering smart charging mode of EV (b) comparison of power generated by DGU in case 3 and case 4 in LGPS considering smart charging mode of EV.

6.3.2. EV with EV2G mode

In this mode, an EV's capability of supplying power to the home appliances is utilized. Cases 1-4 are further analyzed considering EV2G mode of EV. Tables 6-8 present the system load, PAR, and comfort of the consumers in different pricing schemes considering EV2G mode.

Table 6. Comparison of system cost in different pricing schemes considering EV2G mode.

Case	System cost (INR)		
	LPS	LGPS	PLPS
Case 1: Home appliances	1187.84	1102.12	1181.00
Case 2: Home appliances + SD	1175.90	1086.07	1167.97
Case 3: Home appliances + DGU	1019.81	920.28	1013.20
Case 4: Home appliances + SD + DGU	965.19	860.82	951.95

Table 7. Comparison of PAR of system load profile in different pricing schemes considering smart charging mode of EV.

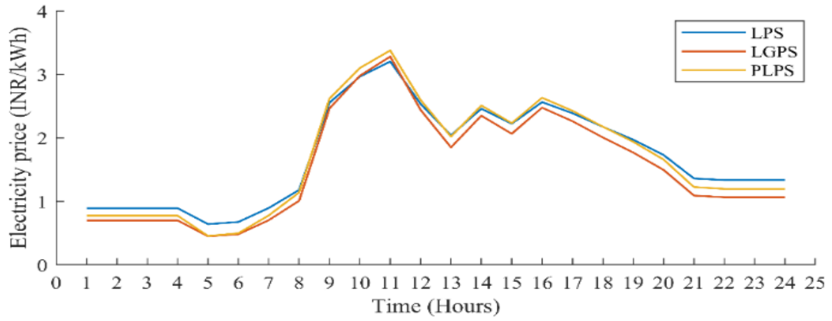
Case	PAR of system load profile		
	LPS	LGPS	PLPS
Case 1: Home appliances	1.719	1.718	1.719
Case 2: Home appliances + SD	1.693	1.688	1.694
Case 3: Home appliances + DGU	1.684	1.670	1.687
Case 4: Home appliances + SD + DGU	1.545	1.539	1.534

Table 8. Comparison of discomfort index in different pricing schemes considering EV2G mode.

Case	Discomfort Index		
	LPS	LGPS	PLPS
Case 1: Home appliances	2439.34	2429.16	2443.70
Case 2: Home appliances + SD	2428.01	2423.03	2422.99
Case 3: Home appliances + DGU	2442.11	2437.29	2434.65
Case 4: Home appliances + SD + DGU	2444.94	2441.27	2456.12

Case 1: When the system cost in Table 3 and Table 6 is compared, it is seen that system cost in EV2G mode is less as compared to smart charging mode in all pricing schemes and cases 1-4. From Table 6, it is observed that in case 1, the system cost is minimum in LGPS. The prices achieved at the equilibrium point in case 1 considering EV2G mode are shown in Fig. 8(a). Hourly electricity price in LGPS is minimum among all pricing schemes except the 11th hour. Hence, the system cost is also minimum in LGPS. When EV operates in EV2G mode, EV feeds power to the home appliances during the 17-20th hour. Fig. 8(b) illustrates the power drawn by the EV battery. A positive value of power means power is charged into the EV battery. A negative value represents the power is discharged from the battery to the home appliances.

A comparison of total system load in LGPS in case 1 considering smart charging mode and EV2G mode of EV is shown in Fig. 8(c). In EV2G mode, system load is reduced during the 15-20th hour and is increased from 21st hour to 6th hour in the morning the next day. Reduction in cost during peak hours is more than the increase in cost during off-peak hours. Hence, the total system cost in EV2G is reduced by 5.65% from the system cost in smart charging mode in case 1. In case 1, PAR of the system load and DI of the consumers are minimum in LGPS among all the pricing schemes, as shown in Tables 7 and 8.



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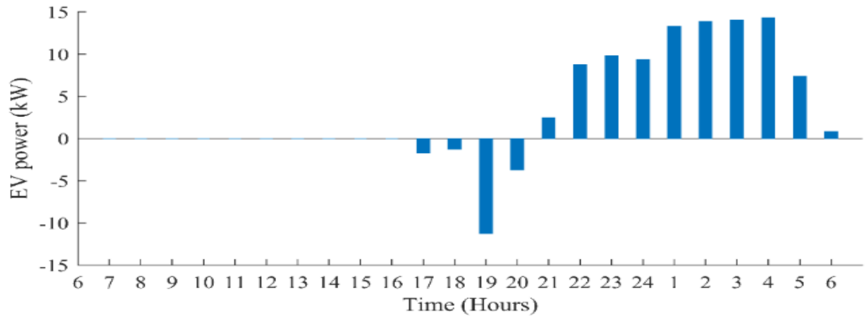

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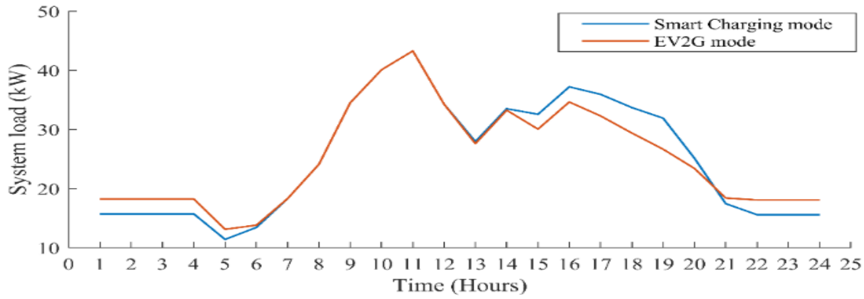
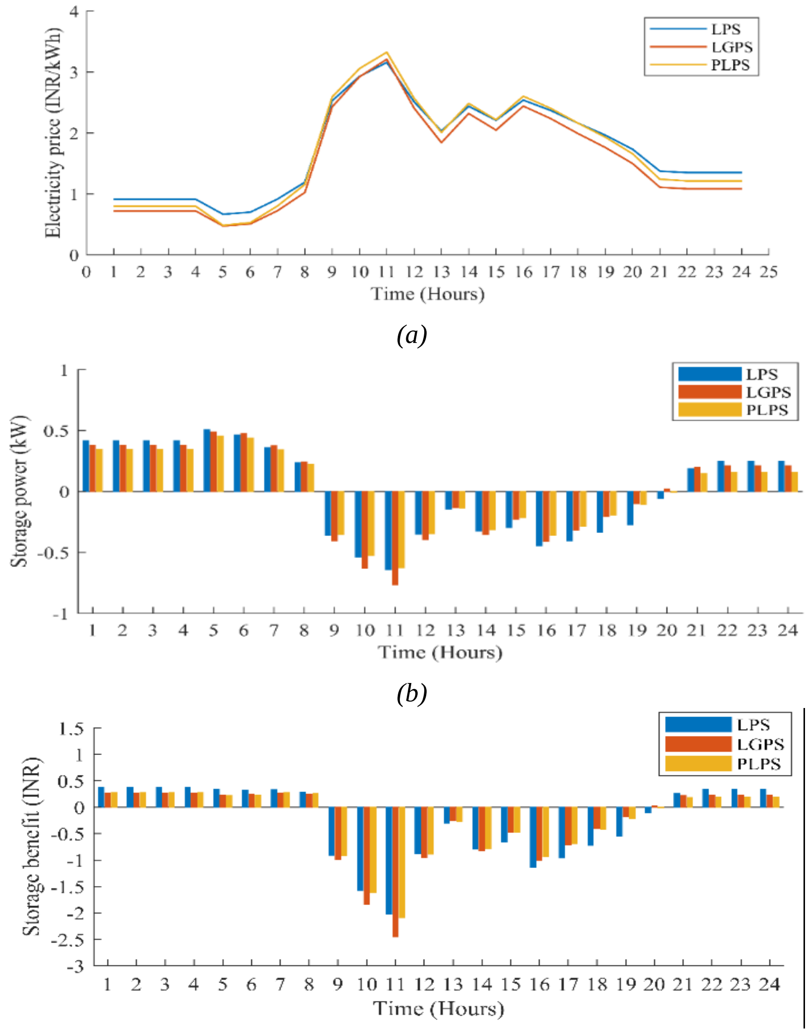


(c)

Figure 8. (a) Electricity price in different pricing schemes in case 1 considering EV2G mode, (b) EV charging/discharging power in LGPS in case 1 considering EV2G mode (c) total system load in LGPS in case 1 considering smart charging mode and EV2G mode.

Case 2: In this case, the demand flexibility of consumers with SD is calculated considering EV2G mode of EV. Among the three pricing schemes, the total cost of consumers with SD and EV2G capability is minimum in LGPS. The electricity price in case 2 considering EV2G capability is shown in Fig. 9(a). The price of electricity is the lowest in LGPS. Hence, the electricity cost is minimum in LGPS. The power drawn by SD and hourly cost of SD during three pricing schemes are shown in Fig. 9(b) and Fig. 9(c), respectively. The cost of charging SD is less during off-peak hours, and profit of discharging power from SD is large during peak hours. Table 6 shows that the system cost of consumers with SD in the three pricing schemes is 1.0%, 1.45%, and 1.10% less than the consumers without SD, respectively. The profit of SD is maximum in LGPS. It is observed from Tables 3 and 6 that the system cost in case 2 in the three pricing schemes is 4.23%, 5.39%, and 4.56% less in EV2G mode than in smart charging mode. It is due to the discharging capability of EV. The maximum benefit of EV2G capability of EV is achieved in LGPS.

Table 7 shows that the PAR of system load for consumers with SD and EV2G capability. Though the PAR values in all the pricing schemes are close, the minimum PAR of 1.688 is achieved in LGPS. Table 8 represents the discomfort caused by the optimal appliance schedule suggested by EMCS considering EV2G capability. It is observed that the consumers with SD experience minimum discomfort in PLPS. The discomfort in LGPS is slightly higher than in PLPS.



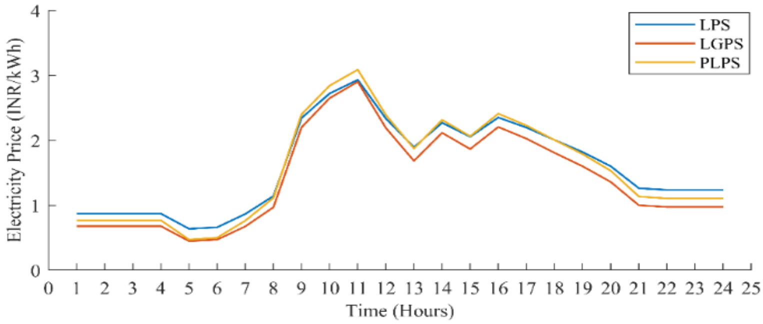
(c)

Figure 9. Hourly variation of (a) electricity price (b) storage charging/discharging power (c) cost of power drawn by storage in different pricing schemes in case 2 considering EV2G mode.

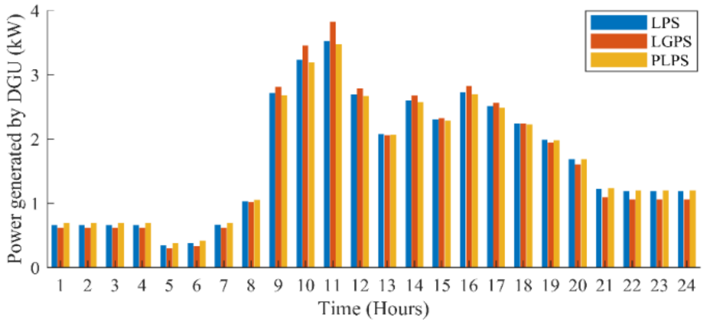
Case 3: In this case, the contribution of DGU and EV with EV2G capability in energy management of consumers is evaluated. Table 6 shows that the total cost of consumers with DGU is 14.14%, 16.50%, and 14.20% less than the system cost without DGU. Moreover, savings achieved with the addition of DGU in the system is considerably higher than the saving earned in the presence of the only SD. This is because SD buys energy from the grid during off-peak hours and supplies that energy to the consumer during peak hours, whereas DGU only discharges the generated energy. The DGU also reduces the system's net demand and hence the price of electricity. Therefore, the savings acquired by DGU is more.

It can also be observed that among all the pricing schemes, the consumers with DGU receive minimum cost in LGPS. Fig. 10(a) shows that the hourly electricity price in LGPS is the lowest among other pricing schemes. Fig. 10(b) illustrates the hourly power generated by DGU in different pricing schemes in case 3, considering EV2G mode. The total power generated by DGU in a day is equal to its maximum generation capacity in all the pricing schemes. Using the electricity price and power generated by DGU, the benefit of each DGU is obtained. It is found out to be higher in LPS and PLPS. However, due to the minimum electricity price, the system cost is minimum in LGPS.

Tables 3 and 6 show that the total cost of consumers with DGU in EV2G mode is less than in smart charging mode. The expenses of consumers with DGU in LPS, LGPS, and PLPS are 4.27%, 5.40%, and 4.18% less in EV2G mode than in smart charging mode. From Table 7, we observe that the PAR of the system load profile in LGPS is 1.670, which is the minimum among all pricing schemes. It is also observed that the PAR of the system load profile in case 3 is improved compared to case 1 and case 2. Table 8 shows that in case 3, the consumer discomfort in LGPS is higher than the discomfort in PLPS.



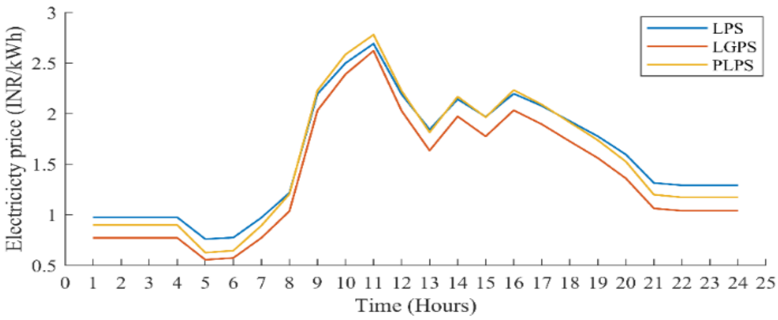
(a)



(b)

Figure 10. Hourly variation of (a) electricity price (b) power generated by DGU in different pricing schemes in case 3 considering EV2G mode.

Case 4: In this case, we analyze the results of energy management for consumers with SD, DGU, and EV with EV2G mode in different pricing schemes. Firstly, the impact of DEMS on system cost is observed. Table 6 shows that the system cost in case 4 is minimum in LGPS. The least cost in LGPS is attributed to the minimum hourly price of electricity in LGPS. It can be seen in Fig. 11(a). A comparison of storage power in cases 2 and 4 in LGPS considering EV2G capability is shown in Fig. 11(b). The figure shows that the SD is more efficiently utilized in case 4 compared to case 2. Fig. 11(c) illustrates that the power generated by DGU in case 3 and case 4 in LGPS. The figure shows that more energy is generated by DGU in case 4 during peak hours than in case 3. Therefore, the benefit of DGU is more in case 4 as compared to case 3 in LGPS.



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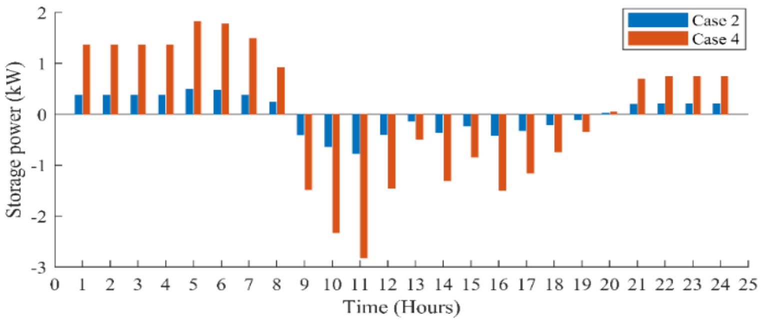

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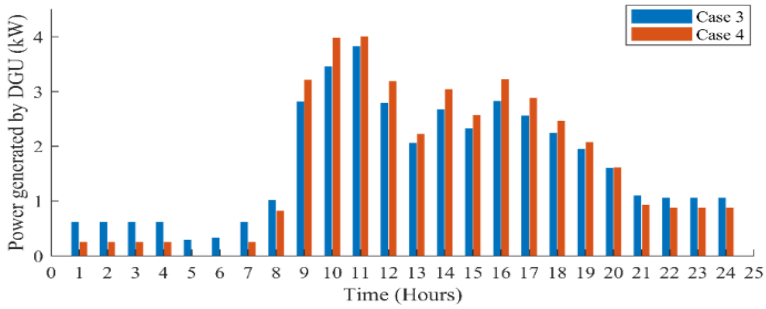
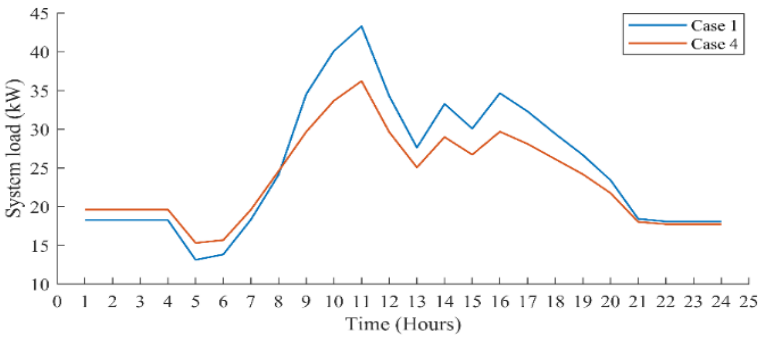


(c)

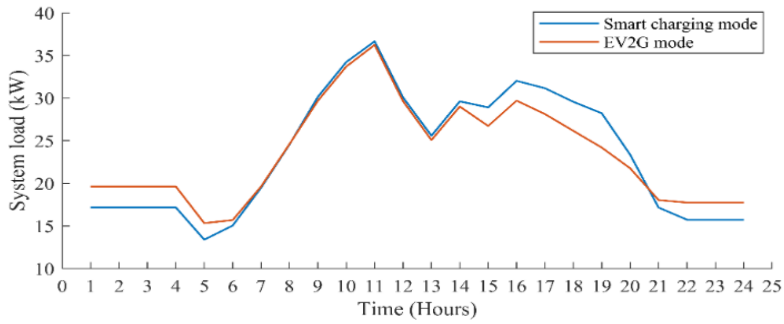
Figure 11. Comparison of (a) electricity price in different pricing schemes in case 4 (b) storage charging/discharging power in case 2 and case 4 in LGPS (c) power generated by DGU in case 3 and case 4 in LGPS considering EV2G mode.

From Table 6, it is noticed that in a system considering EV2G capability, the total cost in case 4 is 18.74%, 21.89%, and 19.39% less than in case 1 for the three pricing schemes. It shows the maximum savings are achieved in LGPS. The impact of SD and DGU on system load is visualized in Fig. 12(a). The figure presents the hourly variation of system load for cases 1 and 4 in LGPS considering EV2G mode of EV.

The system cost of consumers considering smart charging mode and EV2G mode is also compared for case 4 using Table 3 and Table 6. It reveals that EV discharging capability brings the total cost of the system down by 4.16%, 5.42%, and 4.63% of the system cost attained considering EV's smart charging mode. A comparison of system load considering smart charging mode and EV2G mode for case 4 in LGPS is shown in Fig. 12(b).



(a)



(b)

Figure 12. (a) Comparison of system load of case 1 and case 4 in LGPS considering EV2G mode of EV (b) Comparison of system load in case 4 for smart charging mode and EV2G mode considering LGPS.

Table 7 shows that the PAR of the system load considering EV2G mode is minimum in PLPS. However, total discomfort experienced by the consumers with SD, DGU, and EV considering EV2G capability is minimum in LGPS.

Summarizing the results, we can say that among the three pricing schemes, LGPS is the most suitable pricing scheme for the consumers in terms of system cost and PAR of system load. System cost, PAR, and consumers' comfort are affected by choice of consumers in operating EV in smart charging mode and EV2G mode.

In smart charging mode,

- System cost in cases 1-4 is minimum in LGPS.
- PAR of the system load is minimum in LGPS from cases 1-3 and in PLPS for case 4.
- Consumer discomfort value is minimum in LPS for cases 1-3 and LGPS for case 4.
- Consumers in case 4 have lower system cost, PAR, and higher discomfort than the consumers in cases 1-3 in LGPS.

In EV2G mode,

- System cost in cases 1-4 is minimum in LGPS.
- PAR of the system load is minimum in LGPS from cases 1-3 and in PLPS for case 4.
- Consumer discomfort value is minimum in LGPS for cases 1, 4, and PLPS for cases 2, 3.
- Consumers in case 4 have lower system cost, PAR, and higher discomfort than the consumers in cases 1-3 in LGPS.

7. CONCLUSION

In this study, a DEMS is presented for residential consumers to observe the impact of dynamic pricing schemes on the system performance. Three pricing schemes considered are linear, logarithmic, and penalty-based linear pricing schemes. The coefficients of the price functions are selected such that all the pricing schemes have the same average cost initially. The performance of the DEMS is evaluated in terms of system cost, PAR, and consumer comfort. The EMP is formulated using a non-cooperative game, and the proximal decomposition algorithm is used to obtain the Nash equilibrium of the game. The results are extensively discussed using four different cases. The cases are categorized based on the different types of resources owned by the consumers. The case study involves consumers without SD and DGU, consumers with only SD or DGU, and both SD and DGU. In this study, two different modes of operation of EV, i.e., smart charging mode and EV2G mode of operation, are considered. The results present that the LGPS scheme appears to be the most economical for all types of consumers irrespective of the EV's mode of operation. LGPS is the best scheme in terms of PAR of the system load except for consumers with SD and DGU. PAR for consumers with SD and DGU is the lowest in the PLPS scheme.

Consumer comfort depends on the chosen mode of operation and the type of the consumer. The results show that the system cost, consumer comfort, and PAR work in a complementary manner.

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