Electric Vehicle Scheduling Strategy in Residential Demand Response Programs With Neighbor Connection

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***Abstract*—As smart grid enablers, demand response programs for household purposes have been in highlight recently. This paper presents a detailed structure of a household user, which is capable of energy transactions among consumer and load-serving entity. The proposed household model comprises several assets including nonshiftable appliances, shiftable appliances, and electric vehicle (EV). The EV can further contribute to the vehicle-to-home and vehicle-to-grid type of connections that can reduce the household electricity payments with their bilateral energy transactions. The day-ahead dynamic prices are superimposed with peak power limiting approach to prevent the formation of new peaks. The energy transaction among neighbor enhances the reduction in daily energy payments and flexibility among users. The centralized optimization problem is formulated as mixed integer linear programming problem. The validity of the proposed system can be proven by performance evaluation of simulation results.**

***Index Terms*—Demand response (DR) programs, electric vehicle (EV), smart grid, vehicle-to-grid (V2G), vehicle-to-home (V2H), vehicle-to-neighbor (V2N).**

Nomenclature

$k(K)$	Index (set) of household user.
$t(T)$	Index (set) of time periods.
$C_{t,\text{buy}}$	Electricity price for purchasing energy from grid.
$C_{t,\text{sell}}$	Electricity price for selling energy to grid.
$E_{k,t}^{\text{grid}}$	Energy consumed by kth user from grid in t time slot.
$E_{k,t}^{\text{NS}}$	Energy consumed by nonshiftable appliance of user k in t time slot.
$E_{k,t}^{S}$	Energy consumed by shiftable appliance of user k in t hour.
$E_{k,t}^{\text{ev,C}}$	Energy consumed by EV for charging of user k in t hour.
$E_{k,t}^{\text{ev,D}}$	Energy consumed by EV for discharging of user k in t hour.
$\widehat{E}_{k,t}^{\text{ev}}$	Energy rating of EV of user k in t hour.
η_{ev}^{D}	Discharging efficiency of EV.
η_{ev}^{C}	Charging efficiency of EV.
T_a	Arrival time of EV.
T_d	Departure time of EV.
E_{trip}	Energy consumed in a trip.
$E_{k,\max}^{\text{ev}}$	Maximum energy required by EV for user k.
$E_{k,\min}^{\text{ev}}$	Minimum energy required by EV for user k.
$\text{EL}_{k,t}^{\text{ev}}$	Energy level required for EV of user k in t hour.
$\text{EL}_{k,\min}^{\text{ev}}$	Minimum energy level required for EV of user k.
$\text{EL}^{\text{initial}}$	Initial energy level required for EV.
E_{charge}	State of charge for EV.
B	Binary variable for EV charging and discharging.
$E_{k,t}^{\text{load}}$	Energy consumption for shiftable and nonshiftable appliances.
α	Service charge for using grid infrastructure.
$E_{k,t}^{\text{ev,onr}}$	Energy requirement of owner EV.
$E_{k,t}^{\text{nbr}}$	Energy requirement of neighbor seeking energy purchase.
$E_{k,t}^{l,\text{nbr}}$	Individual energy requirement of owner seeking to sell energy.
L_{peak}^{U}	Peak load of unscheduled consumption.
L_{peak}^{S}	Peak load of scheduled consumption.
L_{valley}^{S}	Valley load of scheduled consumption.
L_{mean}	Mean value of load.
L_{total}^{S}	Total scheduled load.
L_{total}^{U}	Total unscheduled load.
γ	Coefficient for allowed margin.

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I. Introduction

The smart grid is an extended version of the existing grid which features an automatic and controllable self-driven system. These systems are very useful as they can lead to highly resumable operation in the network. In the peak hours, high power demand has been observed. The generation companies are required to install new plants to fulfill the demand. The demand-side programs are found to be as a solution to this problem. These programs allow customers to become a part of the electricity network. Demand-side programs have been implemented for the commercial, industrial, and residential type of users in the past. According to a survey done by the U.S. Department of Energy Information, around 40% of the total power consumption was employed in residential and commercial buildings [1]. It will be highly beneficial for companies to encourage the residential customers to participate in demand-side programs. The customers will also get benefits if they get associated with such programs.

The term demand response (DR) is defined as "voluntary change of demand." The change is considered as the reduction of the load demand when the energy price rises, i.e., the customers will get profit on their energy bill by reducing the energy requirement. DR programs can be of two types: First is based on reliability and economic factors, e.g., direct load control programs [2]. Another type of DR is price-based programs. In this study, the focus is concentrated on price-based DR programs. For the implementation of these programs, communication is struggling part, where advanced metering infrastructure (AMI) has emerged. AMI is a framework to facilitate the automatic bidirectional communication among energy provider companies and energy customers [3]. The objective of AMI is to communicate the information regarding energy consumption data and allow the users to make informed preferences about usage based on the price at a particular time.

A. Literature Review

In demand-side programs, the user varies their demand according to the variations in electricity prices, and correspondingly the peak electric load gets lessened. Consumers can shift their demand toward off-peak hours with the help of home energy management (HEM) system. Over the years, research is being practiced on the enactment of HEM system. In this framework, the HEM system [4] is developed to determine the optimal power scheduling so it can be delivered to each electric appliance by the home gateway. The study in [5] has evaluated an HEM system by considering the electric and thermal constraints prescribed by overall power balance and consumer preferences. The optimization-based HEM controller, incorporating several classes of domestic appliances including deferrable, curtailable, thermal, and critical ones, is developed in [6]. The electric storage space heating for customers to minimize the electricity price and to maximize the profit is analyzed in [7]. The different optimization platforms to study DR programs, such as game theory [8], heuristic-based evolutionary algorithm [9], and mixed integer linear programming (MILP) [10], comprise a part of the literature.

A DR model for residential electricity user is presented in [11], where the objective is designed as to maximize the net consumer benefit with comfort by using different utility benefit functions. In [12], a dual DR function of different household agents is modeled and solved using distributed gradient algorithm. The study in [13] has analyzed domestic DR using a modified genetic algorithm under the penetration of renewable distributed generation and storage. To analyze a daily load behavior pattern of an individual household user, a very short term load forecasting method with 30 min forecasting horizon is proposed in [14]. But, it is disadvantageous because it results into the higher forecasting accuracy of the aggregated demand compared to the individual household. In [15], a scenario of forecasting load pattern aiming to analyze the impact of distinct pricing signals on the end-user load is proposed, but it fails to provide uncertainty measures in end-user load on their appliance basis. The user convenience model as a nonconvex problem is proposed in [16] and reformulated into convex to optimize the electricity bill.

Recent trends have led the emergence of a new concept of electric vehicles (EVs) in the world of automotive industry. The environmental benefits of EVs and impact on the carbon emission level have taken it into the limelight [17], [18]. To analyze the potential of EVs usage in the power system, it is important to know when to charge and when to discharge them. It leads to their application in DR programs where the solution for the scheduling time is explored [6]. The EV can also be used in the vehicle-to-grid (V2G) mode where the electrical energy stored in the EV battery can also be sold back to the electricity grid [19]. To determine the real-world randomness to the EVs availability for household user a demand shaping problem is proposed in [20], which incorporates the V2G technology in the game environment. The inclusion of an energy storage system with EV, which can further reduce the electricity cost by imposing hard and soft peak power limiting DR strategies, is discussed in [21]. All the mentioned studies are limited to the operation of small number of users and fail to attempt the smart charging for EVs among a large number of households in DR programs.

A multiagent-based decentralized method is proposed to aim at energy sharing among smart homes [22]. The system considered utilization of renewable sources with the storage unit, and energy sharing is done via home batteries, which can provide energy for neighbors. While this paper does not consider the EV as the home asset, the home to grid technology is not available during energy schedule. The self-generation of household is managed by solar radiation that is not available in the winters; this can affect the energy sharing algorithm. The work in [23] has described a coordination operation of household, which consists of EV, storage, and renewable generation. This paper considered the vehicle-to-home (V2H) and V2G connections among three number of users. The study provides the insight of energy sharing among household; however, the numerical aspect does not reveal the benefits gained by the home user for different energy transactions.

Nowadays due to emerging EVs, the fast charging stations have become a point of the competitive environment in the automotive market. The supercharging of an electric car is almost equivalent to 120 houses coming online for half an hour, where the average energy consumption of a household in the USA is around 19 kWh per day, according to the U.S. Energy Information Association [24]. A supercharging process does not take more energy to charge; it just makes charging faster, but when it comes to the electricity grid, it can become a severe issue. Therefore, this kind of problem leads to the need for smart charging so the grid burden can be avoided.

The above-mentioned literature reveals that the smart charging of EV is not incorporated by researchers in the framework of residential DR. It encourages to look for further research for EV smart charging purposes. The energy sharing approach has been recognized by very few studies such as [22] and [23]. The application of energy sharing among household by the medium of EV is not recognized in the DR framework throughout the literature. Few studies have analyzed the impact of V2G and V2H connections for the household user [6], [19], [20], [21].

But no study has analyzed the impact of vehicle usage as an asset for the economic benefit of the home user.

B. Summary of Contribution

This paper investigates the operation of the distinct type of residential electricity consumer system in DR architecture. Each household user is equipped with the shiftable and nonshiftable type of appliances, whereas some users are also installed with the EV that contributes to V2G and V2H connections. The system operates under the bidirectional information communication between the user and load-serving entity (LSE) by utilizing AMI. The EV arrival time and departure time is determined by the application of Gaussian distribution method. The neighborhood connection named as vehicle-to-neighbor (V2N) is also enabled for a large group of customers with the different types of EVs installed. Here, the exclusive problem of energy consumption scheduling with energy sharing among neighbors is formulated as an MILP for minimizing the total energy cost of the system.

The key contributions of the proposed architecture are as follows.

1) The proposed approach enables the EV smart charging technology among residential customers.
2) Incorporating operation and analysis of power transaction between the energy user and the electricity grid in the DR framework.
3) The inclusion of the concept of the power sharing among neighbors in the residential DR framework.

The rest of this paper is organized as follows. The system modeling of the different components is briefly explained in Section II. The relevant theories are explained in Section III. The case study performed and simulation results obtained to verify the effectiveness of the proposed methodology are presented in Section IV. Finally, the paper is concluded in Section V.

II. System Model

A. Overview of Proposed System

This system presents a group of household customers operating under a smart grid, which entails the LSE and an automatic load control unit (ALCU), as shown in Fig. 1. Each home is installed with ALCU, which is equipped with a built-in smart meter. A group of different types of the customer based on usage is considered. The customers are classified into the following four categories based on their energy consumption in a day.

1) In the first group, household consumes less energy and it occupies two members. This kind of houses is equipped with few appliances.
2) The second group is inhabited by a five-member family in the house. This group consumes comparatively more energy than the low consumption (LC) house of group 1.
3) Any home in group 3 is a high-consumption (HC) household, which is having seven to eight members in the house. It is classified as HC house.
4) The fourth group is classified as very high consumption (VHC) home.

In this study, it is assumed that each household is registered for the net metering system in coordination with LSE to communicate the demand load information and to get day-ahead electricity prices in reverse. The electricity prices considered here are not real prices, although it can give close information to the actual charges. Limited number of the households are equipped with EV at their premises. The EV customers are registered for the V2G, V2H, and V2N type of connections. ALCU of each household handles the bidirectional information for the energy and price communication.

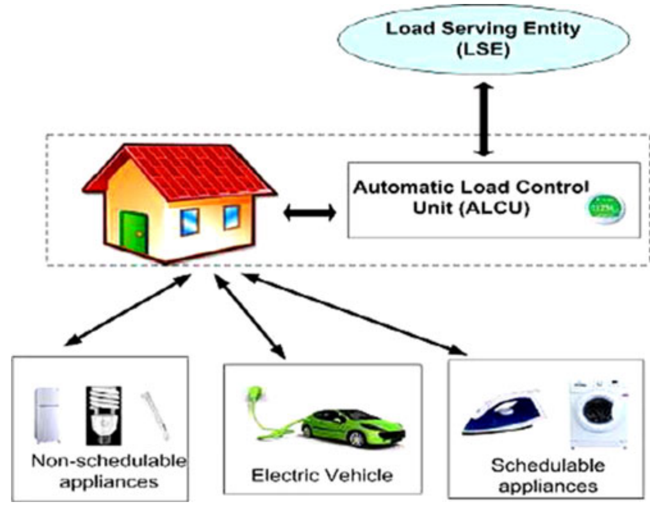

Fig. 1. Block diagram of the proposed system with single household.

In the scenario of V2N connection, each household is connected to the centralized control unit (CCU). The transmission of bidirectional power flow and energy information is updated via CCU. When there is a surplus energy available to a customer, stored in the storage asset, the power flow is enabled to transfer the electricity to the neighborhood through CCU. After that, the CCU can utilize the surplus energy via power transaction to another customer having energy requirement. This type of problem arises in peak hours when LSE is not able to fulfill the demand. As a solution, this concept of selling power from one end consumer to another can enhance the flexibility and benefits for both of them. This idea can also be applicable in times when LSE is serving load at high charges during peak hours. Therefore, a customer can get power from a neighbor at comparatively lower prices. The prices for buying and selling the energy should be same for customers participating in such event.

The degradation of EV battery during charging and discharging is a major concern. Here, it is assumed that depreciation of EV battery is taken care of by EV manufacturer company in battery rental business [25]. The charging of EV can be of two types. First is dumb charging; it is applicable when EVs begin charging immediately after returning from their last journey of the day. Another is smart charging; in this, EVs are charged at low electricity prices during off-peak hours and discharge when electricity prices are high.

B. Mathematical Modeling of System Components

This section presents the mathematical model of the system architecture. The operation of a household is analyzed for a single day. The day is split into equal time divisions and the time horizon for the day is denoted as T and indexed as t.

1) Smart Charging: The objective function of the proposed smart charging is to minimize the total daily cost for energy usage of each household. The cost function described in (1) is the total cost function (TCF) calculated for a day basis for households customer shown as

$$\text{Minimize TCF} = \sum_{k=1}^{K} \sum_{t=1}^{24} C_{t,\text{buy}} \, E_{k,t}^{\text{grid}}. \tag{1}$$

The objective function describes the total cost of procuring any energy transaction between the user and the grid. The energy consumption by user is utilized for their appliance demand and charging of EV. The cost for EV maintenance and other appliances is neglected here.

The minimization TCF of energy demand is subjected to various constraints described in the following way.

a) Power balance constraints: The power balance at each time step within a household is described as

$$P_{k,t}^{\text{grid}} = P_{k,t}^{\text{NS}} + P_{k,t}^{S} + P_{k,t}^{\text{ev,C}} \tag{2}$$

where $P_{k,t}^{\text{grid}}$ is the power supplied by grid. $P_{k,t}^{\text{NS}}$, $P_{k,t}^{S}$, and $P_{k,t}^{\text{ev,C}}$ are the power carried for nonshiftable, shiftable, and EV load, respectively

$$E_{k,t}^{\text{grid}} = P_{k,t}^{\text{grid}} * t. \tag{3}$$

Here, the time sampling is considered as one hour. Equation (2) represents the power balance equation for smart charging optimization framework. In this scenario, the total energy brought from grid $E_{k,t}^{\text{grid}}$ is consumed for the purpose of nonshiftable appliance, shiftable appliance, and EV load demand, which is $E_{k,t}^{\text{NS}}$, $E_{k,t}^{S}$, and $E_{k,t}^{\text{ev}}$, respectively

$$\text{Minimize} \sum_{k=1}^{K} \sum_{t=1}^{24} C_{t,\text{buy}} \left(E_{k,t}^{\text{NS}} + E_{k,t}^{S} + E_{k,t}^{\text{ev,C}} \right). \tag{4}$$

The objective function can be split into two parts as in (4). The first term is responsible for the nonshiftable type of appliances that results no shifting in load. The second part comprises the cost for the shiftable type of appliances and EV that varies. Hence, the total cost is optimized.

b) Electric vehicle: In the smart charging concept, EV is considered only for charging purpose. Here, charging of EV is determined by optimizing the TCF for a day. In general, the charging and discharging equations of EV are represented in (5) and (6), respectively, where η_{ev}^{C} and η_{ev}^{D} are the charging and discharging efficiency of EV, respectively

$$E_{k,t}^{\text{ev,C}} = \frac{\widehat{E}_{k,t}^{\text{ev}}}{\eta_{\text{ev}}^{C}} \tag{5}$$

$$E_{k,t}^{\text{ev,D}} = \widehat{E}_{k,t}^{\text{ev}} * \eta_{\text{ev}}^{D} \tag{6}$$

$$\text{EL}_{k,t}^{\text{ev}} \leq E_{k,\max}^{\text{ev}} \quad \forall t \in [T_a, T_d] \tag{7}$$

$$\text{EL}_{k,t}^{\text{ev}} \geq E_{k,\min}^{\text{ev}} \quad \forall t \in [T_a, T_d]. \tag{8}$$

The maximum and minimum limits imposed on state of energy level of EV are represented in (7) and (8). The charging of EV can only be done when vehicle is at home, i.e., between the arrival time T_a and departure time T_d

$$E_t^{\text{trip}} \leq E_{k,\max}^{\text{ev}} \quad \nexists t \in [T_a, T_d] \tag{9}$$

$$EL^{\text{initial}} + E_{\text{charge}} \geq E_{\text{trip}}. \tag{10}$$

For the purpose of going on a trip, the EV can use maximum energy, i.e., $E_{k,\max}^{\text{ev}}$. The energy required for a trip should always be less than the sum of initial battery level and state of charge, as shown in (10).

2) Vehicle-to-Home: In this scenario, the household energy is supplied by EV during peak periods. The energy supplied from grid is consumed by household appliances and EV as explained in (11). The binary variable B represents 1 if EV is in charging mode and 0 if in discharging mode. The charging and discharging equations of EV are given by (5) and (12), respectively

$$E_{k,t}^{\text{grid}} = E_{k,t}^{\text{NS}} + E_{k,t}^{S} + BE_{k,t}^{\text{ev,C}} - (1-B)E_{k,t}^{\text{ev,D}} \tag{11}$$

$$E_{k,t}^{\text{ev,D}} = \left\{ \begin{array}{ll} E_{k,t}^{\text{ev,D}}, & \text{if } E_{k,t}^{\text{ev,D}} \leq E_{k,t}^{\text{load}} \\ E_{k,t}^{\text{load}}, & \text{if } E_{k,t}^{\text{ev,D}} \geq E_{k,t}^{\text{load}} \end{array} \right\} \tag{12}$$

$$E_{k,t}^{\text{load}} = E_{k,t}^{\text{NS}} + E_{k,t}^{S}. \tag{13}$$

The function in (14) represents final objective for V2H mode. The negative sign represents that the energy is supplying to home by EV

$$\text{Minimize} \sum_{k=1}^{K} \sum_{t=1}^{24} C_{t,\text{buy}} \Big(E_{k,t\ \text{fixed}}^{\text{NS}} + E_{k,t}^{S} + E_{k,t}^{\text{ev,C}} - E_{k,t}^{\text{ev,D}} \Big). \tag{14}$$

3) Vehicle-to-Grid: In this mode, the energy can be fed back to the grid when household acquires surplus energy at home. The objective function in (15) represents the cost function for this mode. The objective function is split into two parts. The first part is to minimize the total cost of purchasing energy from the grid. The second part comprises the maximization of total revenue obtained by selling energy back to the grid

$$\text{Minimize} \sum_{k=1}^{K} \sum_{t=1}^{24} \Big\{ C_{t,\text{buy}} \left(E_{k,t}^{\text{NS}} + E_{k,t}^{S} + E_{k,t}^{\text{ev}} \right) - (1-\alpha) C_{t,\text{sell}} \, E_{k,t}^{\text{ev,D}} \Big\} \tag{15}$$

where α is the service charge for using grid infrastructure, i.e., usually 5%–15% of selling price of electricity at that time. The service charge depends on the location and the electricity grid. The energy balance equation in (16) shows that B is a binary variable for EV charging and discharging, which can be assigned a value as 1 and 0, respectively

$$E_{k,t}^{\text{grid}} = E_{k,t}^{\text{NS}} + E_{k,t}^{S} + BE_{k,t}^{\text{ev,C}} - (1-B)E_{k,t}^{\text{ev,D}}. \tag{16}$$

4) Vehicle-to-Neighbor: In this mode, the power sharing is enabled from the V2N. The surplus energy available for vehicle can be shared to a neighbor during peak price hours. The objective function for this mode is represented in the following equation:

$$\text{Minimize} \sum_{k=1}^{K}\sum_{t=1}^{24}\Big\{C_{t,\text{buy}}\left(E_{k,t}^{\text{NS}}+E_{k,t}^{S}+E_{k,t}^{\text{ev,C}}-E_{k,t}^{\text{ev,onr}}\right) - C_{t,\text{sell}}E_{k,t}^{\text{nbr}}\Big\}. \quad (17)$$

The energy balance equation is represented by (18), whereas (19)–(21) give the information about the energy required for a neighbor that is transferred by the owner of an EV

$$E_{k,t}^{\text{grid}} = E_{k,t}^{\text{NS}} + E_{k,t}^{S} + BE_{k,t}^{\text{ev,C}} - (1-B)E_{k,t}^{\text{ev,D}} \quad (18)$$

$$E_{k,t}^{\text{ev,D}} = E_{k,t}^{\text{ev,onr}} + E_{k,t}^{\text{nbr}} \quad (19)$$

$$E_{k,t}^{\text{ev,onr}} = \begin{Bmatrix} E_{k,t}^{\text{ev,D}}, & \text{if } E_{k,t}^{\text{ev,D}} \le E_{k,t}^{l,\text{onr}} \\ E_{k,t}^{\text{load}}, & \text{if } E_{k,t}^{\text{ev,D}} \ge E_{k,t}^{l,\text{onr}} \end{Bmatrix} \quad (20)$$

$$E_{k,t}^{\text{nbr}} = \begin{Bmatrix} E_{k,t}^{\text{ev,D}} - E_{k,t}^{l,\text{onr}}, & \text{if } E_{k,t}^{\text{ev,D}} \le E_{k,t}^{\text{load}} \\ 0, & \text{if } E_{k,t}^{\text{ev,D}} \ge E_{k,t}^{\text{load}} \end{Bmatrix}. \quad (21)$$

In the V2N case scenario, it is considered that a vehicle owner is sharing their surplus power to a certain neighbor. But there is a constraint that neighbor will only consume power from vehicle owner when the offering electricity prices are less than the grid electricity prices in the particular time period. In (17), $C_{t,\text{buy}}$ denotes the electricity buying price, which is a real-time price offered by LSE on a day-ahead basis, whereas $C_{t,\text{sell}}$ denotes the energy selling price to a neighborhood consumer. Here, for a particular scenario this $C_{t,\text{sell}}$ is fixed. The concept can be simplified as the neighbor consumer seeking for energy demand will only purchase energy from another consumer if the offering prices are less than the grid prices for a particular hour. This concept will be proven beneficial when the grid energy prices are very high during peak hours. In the peak hours, a neighbor can purchase the energy from another consumer, particularly vehicle owner. The selling price can be decided on the basis of peak demand and peak energy prices at different times.

C. Power Transaction Limits

The power transaction limits are imposed on each type of connection. The upper and lower limits of peak load are defined in (22) and (23), respectively. The margin is defined on the basis of (24)

$$L_{\text{peak}}^{S} \le L_{\text{mean}} + \text{Margin}$$
$$L_{\text{valley}}^{S} \ge L_{\text{mean}} - \text{Margin} \quad (22)$$

$$L_{\text{total}}^{U} = L_{\text{total}}^{S} \quad (23)$$

$$\text{Margin} = \frac{L_{\text{peak}}^{U} - L_{\text{mean}}}{\gamma} \quad (24)$$

where γ is the coefficient of allowed margin, which can be interpreted as follows:

If $\gamma = 2$, allowed margin is 25% of previous peak:

1) Lower the margin, better the peak to average ratio (PAR) but lower the consumer benefits.
2) Higher margin means better consumer benefit but less improved PAR.
3) Therefore, a balanced γ should be chosen, so there could be balance restored in PAR and consumer benefit.

III. Preliminary Theory

A. Privacy Control Mechanism

In this paper, a centralized optimization framework is implemented for residential DR. A CCU is developed to operate the energy transaction related information flow. However, the usage of the centralized controller makes it privacy vulnerable for each user. The privacy control mechanism for maintaining each user privacy should be built-in. A privacy protection algorithm named as ElecPrivacy can be developed to protect the privacy of the collected user data from smart meter [26]. ElecPrivacy system can be made of comprising the main subsystems such as metering mechanism, event detection, privacy protection algorithm, and power routing. The metering mechanism obtains a set of energy consumption events. It can also be attached to different load and information from smart meter can be extracted by using signature analysis method. Event detection can detect the switch ON–OFF event for a particular appliance. Privacy protection algorithm enables power routing to identify a detected consumption event. Power routing combines a private user information to the utility to meet demands. By executing ElecPrivacy algorithm in the proposed system architecture, the user privacy can be maintained to certain levels.

In the past, many techniques have been developed to secure the privacy of the user in centralize system framework. One method as developed in [27] has proposed a "privacy metric," which configures that the degree of data availability (accuracy of readings, time resolution, types of readings, etc.) can provide a reliable indicator of overall privacy. To build privacy metric, a list of the important parameter is defined by a system operator on the basis of their priority on home/business owners' expectations of privacy. Expectations of privacy, in turn, are partially based on previous abuse incidents. After the deciding important parameter list, a value can be assigned to it and the sufficiency of available data can be determined on the basis of the requirement. A nonintrusive load monitoring system can further process the data to determine the operating schedules of individual electrical appliances. With the implementation of the above-mentioned privacy metric, the privacy of individual can be maintained in the centralized DR.

B. EV Uncertainty Capture Model

In this paper, the uncertainties are considered to generate the appropriate input scenarios for EVs arrival and departure time. The realization of the uncertain variables is modeled through Gaussian distribution method. This distribution is widely used for arrival time and departure time [28].

The data for EV arrival and departure time have been taken from [28]. The arrival and departure time is plotted in Fig. 2. The Gaussian distribution employed here consider the arrival time with the mean of 19.62 and standard deviation of 3.62. The departure time is considered with 10.53 mean and 3.26 standard

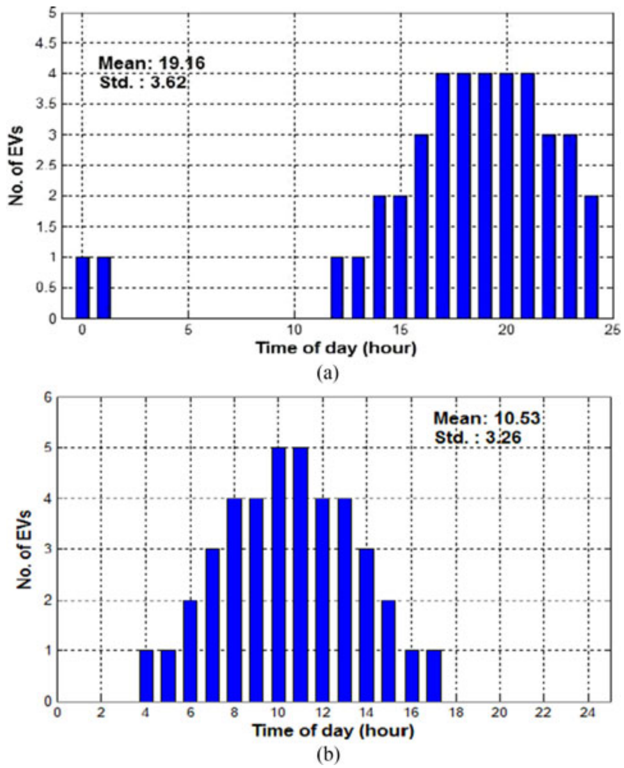

Fig. 2. Daily driving statistics (a) arrival time and (b) departure time.

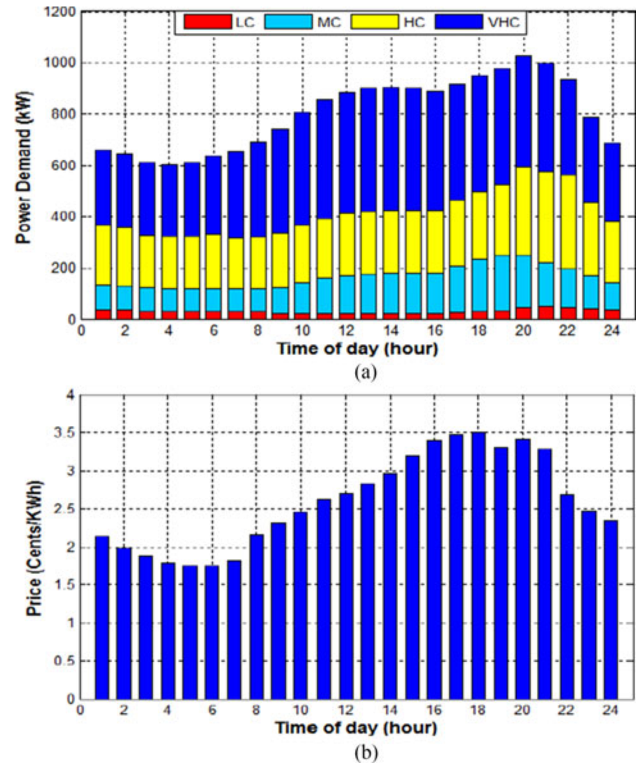

Fig. 3. (a) Residential power demand profile and (b) dynamic price signals.

deviation. The range should be maintained that the departure time must be greater than or equal to the sum of arrival time and the required charging time.

IV. Performance Evaluation and Result Discussion

A. Input Data

The optimization problem for total cost minimization is formulated as MILP aimed to reduce the daily bill of the user. Each household user is operating with their individual ALCU and controlling their energy expenses and load, although there is one centralized unit operating for every user and managing the operations in a centralized fashion. The MILP optimization problem is solved using CVX version 2.0 beta [29] on the MATLAB platform.

In the simulation, 100 household consumers of different type have been considered. The houses are divided into four groups. The number of user is occupied as 40, 40, 15, and 5 in LC, midconsumption (MC), HC, and VHC, respectively. The total load data are taken from BGE suppliers [30]. The total demand for the different type of users based on their consumption is shown in Fig. 3(a).

The household is assumed to be contracted for the day-ahead pricing from LSE via AMI technology. For day-ahead pricing scheme the load demand of consumers is updated to LSE, and in return, the price signals are informed to the user for next day. Price information is highly volatile, and to get future price information, the prediction techniques are needed. The future price can be predicted by applying prediction techniques. The price signal used for the day-ahead pricing is taken from Ameren Illinois Power [31], as shown in Fig. 3(b).

TABLE I
EV Data

Parameter	Tesla Roadster	BMW Mini E	Think City	Chevy Volt
Capacity [kWh]	53	35	28.3	16
Maximum usable capacity [kWh]	47.7	31.5	25.5	14.4
Min capacity [kWh]	5.3	3.5	2.83	1.6
Charging and discharging efficiency [%]	0.93	0.93	0.93	0.95
Full charging time [h]	3.5	3	13	5.1
V2G discharging time [h]	3.5	3	13	5.1

In the system, each house is not equipped with EV. The capacity of EV in the system is considered based on the practical scene. In a society, different classes of customers exist, therefore it is not possible for everyone to purchase an EV. Therefore, only a few houses are considered to be installed with EV. In total four type of 40, EVs are equipped with the system. The number of EVs installed is 10, 16, 10, and 4 for LC, MC, HC, and VHC user, respectively. The electric cars data and ratings represented in Table I have been taken from [25].

B. Assumptions

The few assumptions taken for the implementation purpose of the proposed system can be briefly explained as follows.

1) The ratio of shiftable loads is considered from 30% to 40% of total amount (randomly selected for users).
2) For the V2H operations, the power required for the house is supplied by vehicle (either load or rated discharge value).

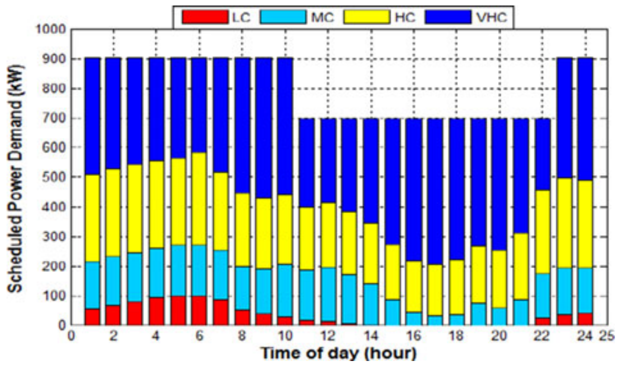

Fig. 4. Residential power demand for shiftable appliance.

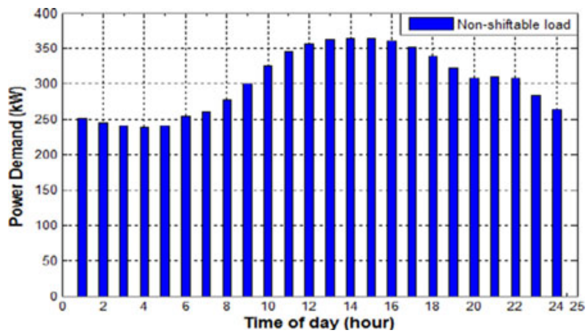

Fig. 5. Residential power demand profile for nonshiftable appliance.

3) For the V2N case, energy to a neighbor is supplied only when the owner meets demand (only surplus energy applicable is send to the neighbor).
4) For the V2G connection, energy fed back to the grid is applicable for peak price times since the frequent charging and discharging of the battery also cause the decrease in life span of the battery.
5) The charging and discharging of the vehicle cannot take place simultaneously.

C. Results and Discussion

The simulation is done for different scenarios to evaluate the EV capabilities applicable for smart charging, V2H, V2G, and V2N connections. In the smart charging scenario, the day-ahead load scheduling with dynamic prices is done. The energy scheduling under varying price encourages the user to shift their energy demand to low price hours.

If all the users try to deviate their load to low price hours, the grid may suffer due to accumulated load. For this purpose, the peak power limiting strategy is applied for scheduling user's load. The total load demand comprises nonshiftable and shiftable type of load, as shown in Figs. 4 and 5. The nonshiftable appliance load cannot be shifted even with time-varying prices, whereas shiftable appliance load is schedulable.

In this paper, two kinds of EV charging is employed, i.e., dumb charging scenario and smart charging. The dumb charging allows the user to charge their EVs at any times when they return at home. But in smart charging, user is participating in optimization process to determine the optimal charging time allocation. It enables the economic benefits to the users in terms of reducing their daily energy bill.

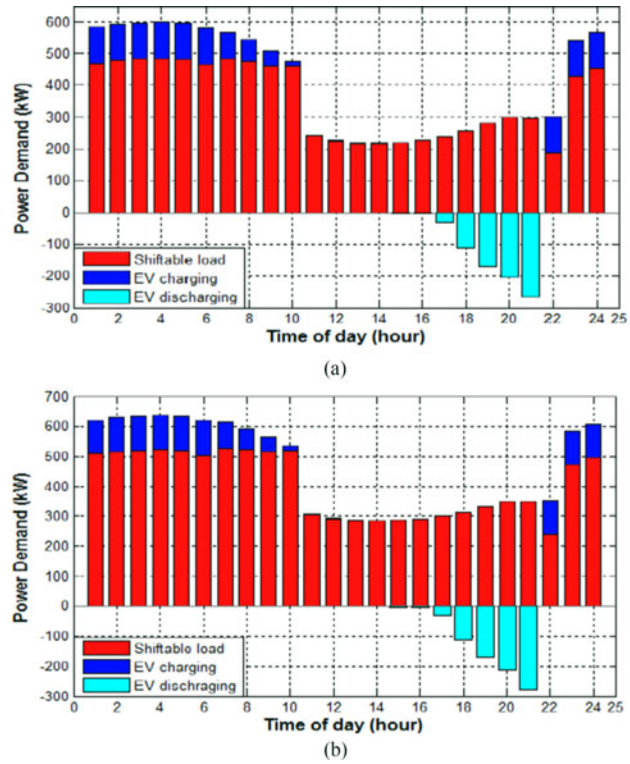

Fig. 6. Load scheduling for a proposed system with (a) V2G connection and (b) V2N connection.

TABLE II
DAILY COST BENEFITS

Operation	Cost benefit (in Cents)	PAR reduction (%)
Smart charging	3100.1	10.2232
V2H mode	5964.1	6.0675
V2G mode	6029.6	5.9673
V2N mode	6029.6	5.9673

For the operation of V2G and V2N connections, the scheduled load is shown in Fig. 6(a) and (b), respectively. The vehicle is charging in off-peak hours and supplying load of the consumer in a high-price region when the owner vehicle is available that time only. However, there are some limitations in V2H connection, i.e., EV will supply only when the discharge rate of EV is greater than the household requirement.

In the simulation results, due to various assumptions, it is observed that the scheduled load appears almost similar when the vehicle is supplying to either home or grid, but the effect of operation can be seen in the daily energy payment shown in Table II. In V2G operation, the household who is supplying power to the grid has to bear the charge for using grid infrastructure.

In the operation of V2N connections, the power transactions are done between the vehicle owner who is having excess energy that can be transferred to a neighbor facing difficulty in scheduling the load at the peak hours when the grid is offering power at high prices. During the V2N operations, some limits have been imposed on energy transaction, i.e., the neighbor will get additional power available only when the EV discharge rate is higher than the total owner house load and neighbor load.

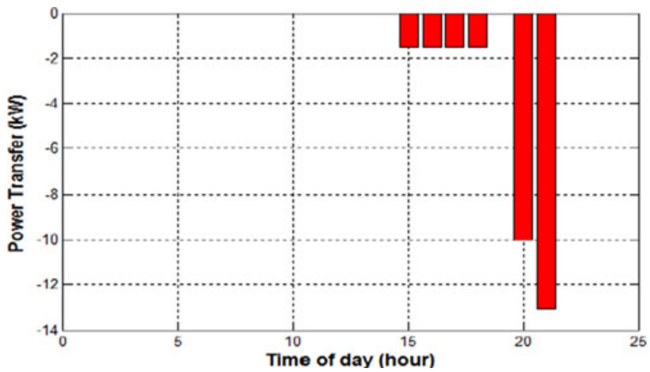

Fig. 7. Power shared to neighbor.

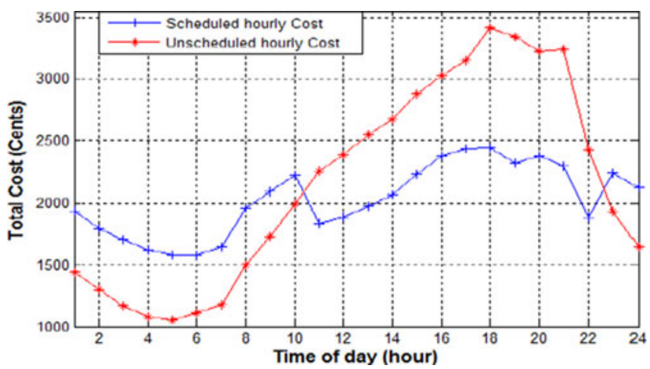

Fig. 8. Hourly cost benefit for the proposed system with smart charging.

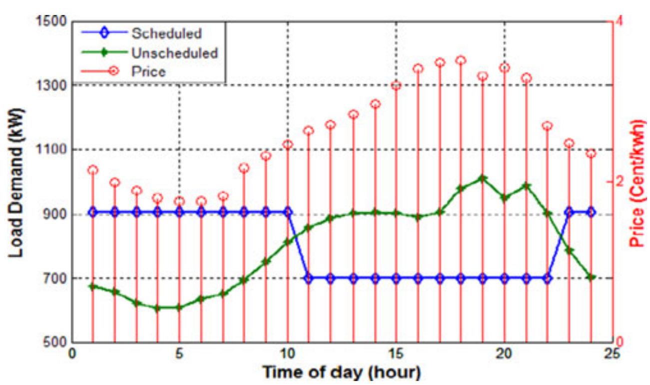

Fig. 9. Load demand on hourly basis for the proposed system with smart charging.

The power shared to a neighbor in V2N connection is shown in Fig. 7.

It is shown in Fig. 6(b) that the discharging of EV is occurring during evening 5–10, this is the period when vehicle with surplus storage can supply to the neighbor. The total cost appeared during unscheduled and scheduled is shown in Fig. 8. It can be analyzed that the hourly cost is reduced during peak hours. The impact of smart charging is also analyzed in terms of cost. The scheduled load shown in Fig. 9 can result in a flattened load curve.

In this context, the benefits to the user on a daily basis are represented in Fig. 10. Here, it is shown that the economic benefit is high for the EV owners as compared to other. The

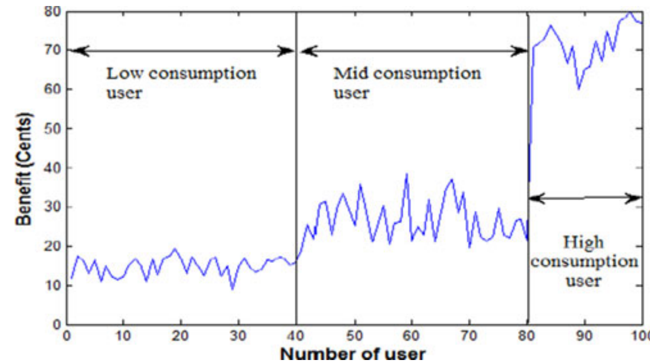

Fig. 10. Total benefits of different class users.

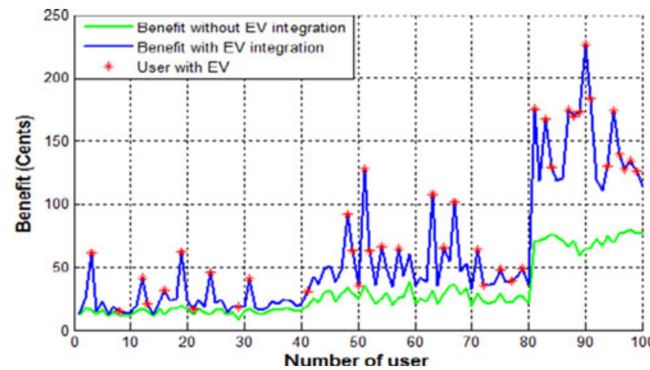

Fig. 11. Benefits of EV integration.

HC users are getting large benefits as compared to LC users because of their capacity and EVs. The selling electricity price from V2N is considered fixed as 3 Cents/kWh.

The influence of using EVs is very high for users in their cost benefits. The results in Fig. 11 can prove the benefits of using EVs as compared to those who do not have EVs. The benefits are also compared for the proposed system with and without EV integration, and it can be seen that the impact of using EVs is very high on system benefits for each user.

The numerical analysis of results for different operating modes is shown in Table II. It can be seen that less change is observed in PAR but total benefits for bill payment is effective for the proposed strategy. The cost benefit is analyzed with respect to base scenario, i.e., without application of optimization or unscheduled load. The cost benefit for smart charging is \$31, whereas for the operating modes V2H, V2G, and V2N, it is \$59.6, \$60.29, and \$60.29, respectively. The cost benefits for V2G and V2N modes are similar because only one mode can operate at a time. The choice of using EVs can affect the user load as well as their total energy bills.

V. CONCLUSION

In this study, the operation of residential energy customers equipped with an ALCU was studied. Under a centralized system, a controller is aimed to minimize the total energy procuring cost with dynamics pricing environment. Furthermore, various operating modes have been analyzed to prove the benefits of the proposed methodology. The bidirection flow of power was considered in this study between each house and LSE, which also contributes to neighborhood communication. The application of the proposed methodology encourages the household user to shift their energy consumption in order to achieve lower daily energy bills. Further integration of vehicles in the transportation environment has introduced the new kind of load in the residential sector, whereas the proposed strategy can develop smooth operations in the scenario. The considered case study can be extended to the practical scenario of several neighbor household. The presented scenario can also be extended to the combination variety of energy user such as residential, commercial, and industrial users. For the future work, the study can also be extended to the testing of the same work in the presence of distribution system where the proposed strategy can affect the whole dynamics of the system.

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