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RESEARCH ARTICLE

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Smart residential energy management system for demand response in buildings with energy storage devices

Abstract In the present scenario, the utilities are focusing on smart grid technologies to achieve reliable and profitable grid operation. Demand side management (DSM) is one of such smart grid technologies which motivate end users to actively participate in the electricity market by providing incentives. Consumers are expected to respond (demand response (DR)) in various ways to attain these benefits. Nowadays, residential consumers are interested in energy storage devices such as battery to reduce power consumption from the utility during peak intervals. In this paper, the use of a smart residential energy management system (SREMS) is demonstrated at the consumer premises to reduce the total electricity bill by optimally time scheduling the operation of household appliances. Further, the SREMS effectively utilizes the battery by scheduling the mode of operation of the battery (charging/floating/discharging) and the amount of power exchange from the battery while considering the variations in consumer demand and utility parameters such as electricity price and consumer consumption limit (CCL). The SREMS framework is implemented in Matlab and the case study results show significant yields for the end user.

Keywords smart grid, demand side management (DSM), demand response (DR), smart building, smart appliances, energy storage

1 Introduction

Recent advancements in the power sector lead the utilities to operate the grid in an efficient, reliable, and safe manner. Further, the adoption of information technology, communication technology, cyber security systems, and internet of things for the betterment of power grid operations, has introduced a new paradigm called smart grid [1]. Different sectors of power system such as generation, transmission, and distribution are being simultaneously updated with the above mentioned technologies to build a smart grid environment. For instance, installation of distributed generation units instead of a centralized one, incorporation of wide area monitoring and control by optimally placing the phasor measurement units in transmission systems, and motivating the end user to take part in the day to day activities of the energy society are a few attempts to achieving a smart grid. Demand side management (DSM) [2] is one of such smart grid activities in which the utility maintains the demand supply balance by directing consumers to change their electricity demand [3]. Further, consumers are encouraged by the utilities to actively participate in the electricity market in order to reduce their electricity bill and avail more benefits from the utility by time scheduling their energy consumption pattern [4]. As a part of DSM programs, the utilities are following various pricing schemes [5] such as two-way tariff (variable price only between peak and non-peak intervals), day ahead pricing, and real time pricing (RTP). In the RTP scheme, the utility announces the electricity price of a particular pricing interval just before that interval begins [6]. On the other hand, few utilities are imposing a time varying consumer consumption limit (CCL) [7] to improve the peak to the average ratio of the system. The consumer is penalized if he/she consumes beyond the predefined CCL of the utility. The alterations carried out by consumers in their consumption pattern as a response to the DSM programs proposed by the utility is termed as demand response (DR) [8]. In DR programs, consumers adjust their demand pattern considering the variations in electricity price and/or CCL so as to reduce the electricity bill and avail more incentives from the utility. The importance and benefits of the DR are discussed in Ref. [9].

Nowadays the utilities prefer to follow the RTP scheme along with the variable CCL in order to obtain more

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economical profit and better reliability in grid operation. In this scheme, the utilities fix a high electricity price and less CCL during peak intervals compared to the non-peak intervals. Hence, residential consumers schedule most of their loads during non-peak intervals without/with compromising their comfort in order to reduce their total electricity bill. As a consequence, the residential consumers are finding an alternate to support their essential demands during peak intervals through energy storage devices. Among various energy storage techniques, battery banks are mostly preferred by residential consumers [10] because of their operational easiness and economic benefits. If charging and discharging operation of battery banks are properly time scheduled, consumers may enjoy a significant reduction in electricity bill without deteriorating the life of battery [11]. This necessitates the use of an energy management system in the residential building with smart home appliances and battery banks.

The impact of smart household appliances and variable energy price on reduction in electricity bill are discussed in Refs. [12–14]. A home energy management system is proposed by Pipattanasomporn et al. to manage the total power consumption below a predefined demand level [15]. In the model proposed, the loads are scheduled as per the user predefined priority and power consumption limit. A mixed integer nonlinear optimization model is developed in Ref. [16] to minimize the total electricity bill in the time-of-use electricity tariff environment. The benefits of battery energy storage are briefly discussed in Ref. [17]. Purvins et al. have discussed the key role of battery management systems in household demand smoothening [18]. The modeling of battery for residential peak demand shaving is presented in Ref. [19]. Further, the authors have tested their model with different residential buildings and the results expressed considerable percentage reduction in peak demand in all cases. Setlhaolo [10] has developed a mixed integer nonlinear programming based optimization model which schedules household appliances along with the battery in order to attain the reduction in electricity bill and peak demand shaving under time of use electricity tariff. Saravanan [20] has proposed a game theoretic energy schedule method to reduce the peak to average power ratio by optimizing the user's energy schedules. The author has expressed that the method proposed is beneficial for both users and power companies. Muratori and Rizzoni [21] have proposed a dynamic energy management framework. In the model proposed, the residential demand is estimated by a novel bottom-up approach and the optimal schedule of all controllable appliances minimizes the consumer electricity related expenditures. An advanced battery management system presented in Ref. [22] is capable of monitoring the voltage, current, power, energy, and state of charge (SOC) for each battery in the array. A new smart energy management algorithm is proposed in Ref. [23] for the hybrid energy storage system (HESS). The HESS contains battery and ultra-capacitor energy storage units. Experimental result shows that the algorithm proposed reduces the operational costs of the energy storage system and increases the system efficiency.

In all the above references discussed, scheduling is performed only for deferrable loads (DLs). However, the operational dynamics of non-deferrable loads (NDLs) will have a major impact on electricity bill, which is not discussed extensively. Further, the consumer behavior on the operation of the DLs is taken as either the time of using probability or from the usage history, which may pose additional operational challenges when the user alters his/her life style. Few authors have included battery as an energy storage device along with the energy management model. However, the optimal scheduling of battery while considering the dynamics of consumer behavior and utility operation is not widely addressed.

It is expected that the optimal scheduling of the DLs along with the battery and due consideration of the operational dynamics of the NDLs shall keep the total demand under CCL, which will save the consumer from penalization. In addition to the optimal scheduling of mode of operation of battery (charging/floating/discharging), if the amount of power exchange in the battery is optimally scheduled, the savings in electricity bill will increase along with the better utilization of the battery. Further, the comfort of the user will be enhanced by acquiring the real time update of the required operational changes of the household loads while scheduling. To attain these goals, a smart residential energy management system (SREMS) is proposed and demonstrated in this paper.

The SREMS proposed assumes that the residence is equipped with household appliances having smart and communication features, battery banks, and a utility interfaced smart meter. The smart meter provides a real time update of the utility dynamics such as variations in electricity price and CCL to the SREMS. The aim of this paper is to develop a real time scheduling algorithm for the DLs and the battery units to increase the savings in electricity bill while considering the operational dynamics of the NDLs, consumer comfort, and utility operational behavior such as variations in electricity price and CCL. The major contribution of this paper are listed as follows: ① the development of scheduling algorithm for the DLs and the battery units to minimize the electricity bill while considering the operational dynamics of the NDLs, the desire and comfort of the user, the operational constraints of the DLs and the battery, the variation in electricity price of the utility, and the operational limit proposed by the utility; and ② the SOC analysis for showcasing the savings from investment cost of battery.

2 Architecture of the system proposed

Presently, residential buildings are filled with different kinds of electrical appliances to increase the comfort of consumers and to complete their tasks in easy and efficient way. On the basis of operating nature and power consumption pattern, residential loads are categorized into three types, namely, essential non-deferrable loads (ENDLs), interruptible non-deferrable loads (INDLs), and DLs.

ENDLs are critical loads which are expected to respond immediately whenever the user needs them. Continuous loads such as building security systems; essential loads such as lighting, fan, personal computer, its accessories and mobile/laptop charging; entertainment loads such as television, DVD player, speaker and home decorates; and kitchen loads such as cooking stove, mixer and toaster are classified as this category. Since the time of operation of these loads in a day is solely dependent on the need and availability of consumers, the time scheduling of these loads may hinder the well-being of users. Hence, the SREMS does not control the operation of the ENDLs. However, the SREMS considers the total demand of all the ENDLs for effective scheduling of other types of loads. Further, the SREMS delivers an alert message whenever the total demand of the ENDLs exceeds the pre-defined limit set by the user.

The second category, the INDLs are thermostatic loads. These loads should maintain the operating temperature at the consumer set value and within the manufacturer defined tolerance limit. Cooling loads such as air conditioner (AC), air cooler, and refrigerator; heating loads such as water heater and space heater fall into this category. The power consumption pattern of these loads is merely dependent upon the consumer availability and seasonal variations. The DLs are non-critical loads which can be flexibly operated anywhere in the predefined time span to complete the task. Considering the operating nature, the DLs are further classified into preemptive deferrable loads (PDLs) and non-preemptive deferrable loads (NPDLs). The PDLs may be operated continuously or discontinuously to complete the given task. The plug-in hybrid electrical vehicle (PHEV), well pump and dish washer are examples of the PDLs. The NPDL should be operated without any interruption once it is started. The cloth washer, cloth dryer, and grinder are examples of the NPDLs.

As discussed in Section 1, residential consumers are interested in energy storage devices (battery) to support the power demand during peak intervals in order to reduce the total electricity bill. The mode of operation of the battery and the power exchange are optimally controlled by the SREMS with due consideration of the operational dynamics of household appliances and utility parameters such as energy price variation and CCL. The block diagram representation of the SREMS proposed is shown in Fig. 1.

Since the operating nature of the ENDLs are merely based on consumers' interest, the SREMS considers all the ENDLs as a single load whose power consumption is time varying. The smart ENDLs module delivers the aggregate demand of all the ENDLs to the SREMS processing unit at regular intervals. Further, this module alerts the user whenever the aggregate ENDLs demand exceeds the

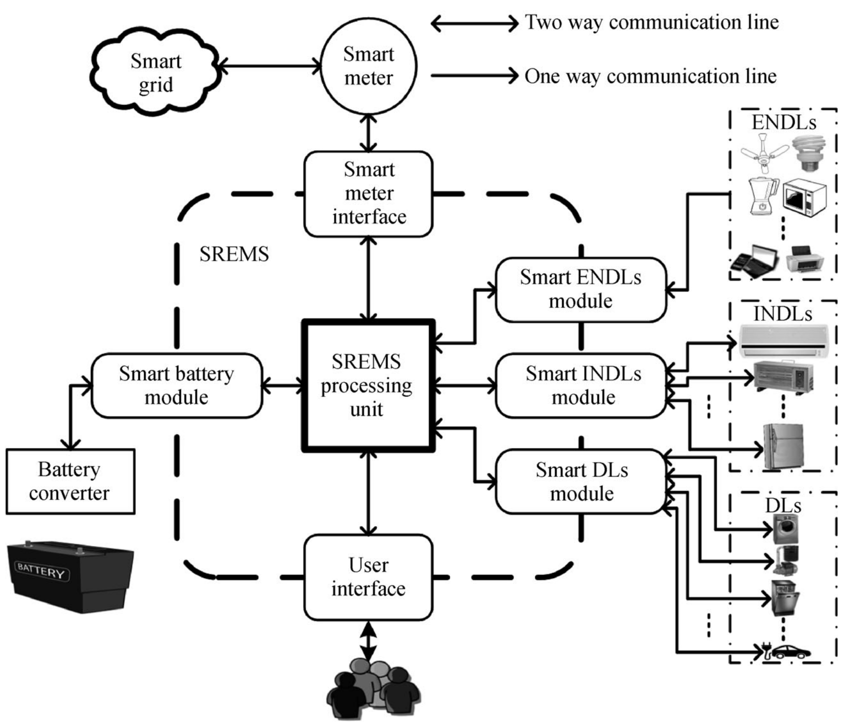

Fig. 1 Architecture of proposed SREMS

predefined limit.

Each INDL has a direct communication with the SREMS through the smart INDLs module. This module receives the information such as power rating for different operating conditions (RUN/STANDBY), tolerance limit, and operating information such as ON/OFF status, set point temperature and operating temperature from each INDL. Further, this module delivers the controlling signal such as RUN/STANDBY to each INDL as instructed by the SREMS processing unit. The smart DLs module interconnects the SREMS with the DLs and updates the information such as the time span of operation and the power rating of the DLs. Further, this module delivers the controlling command (ON/OFF) obtained from the SREMS processing unit as a result of the optimal scheduling algorithm to DLs.

The smart battery module collects the battery specifications such as Ah rating, maximum and minimum limits of charging and discharging current through user interface. Further, it computes the present SOC of the battery. This information is transferred to the SREMS processing unit for further processing. The SREMS dictates the mode of operation of the battery and the amount of power exchange to the battery converter through the smart battery module. The battery converter controls the operation of the battery.

Residential consumers are interconnected with the utility through smart meter which receives the utility updates such as electricity price and CCL at regular intervals. This information is delivered to the SREMS processing unit through smart meter interface. The user interface module helps the consumer to convey their requirements to the SREMS. Further, this module displays the instantaneous total power demand, energy consumption over a period of time, electricity bill and history data such as maximum demand, average demand and, demand variation in previous days. The basic steps involved in the implementation of the proposed model are listed below.

Step 1: Ensure that the residential building is equipped with the smart meter having a two-way communication feature and connected to the utility.

Step 2: Collect the details of household appliances and categorize them into the ENDLs, the INDLs, and the DLs based on their operational characteristics.

Step 3: Ensure that all the INDLs and the DLs are smart loads with communication features and have provision for automatic controls as per the instruction received from the SREMS.

Step 4: Ensure that all the ENDLs are directly interconnected with the smart ENDLs module and every INDL and DL is individually connected with the smart INDLs module and the smart DLs module respectively.

Step 5: Collect the battery parameters: maximum capacity, voltage, operating efficiency, SOC limitation, and operating current limitation.

Step 6: Start and run the SREMS.

Step 7: Fix the user defined parameters such as the amount of power reserved for the operation of the NDLs in all intervals.

Step 8: Define the extended tolerance limit for the INDLs if the user is more concerned about reduction in electricity bill and less concerned about comfort. Otherwise, set this limit to zero.

Step 9: New DLs can be added by updating the operational information such as initialization interval and dead time interval through the user interface module. In addition to this information, the smart DLs deliver the number of intervals required to complete the task and preemptive status of the corresponding DL to the SREMS.

Step 10: The INDLs, the DLs, and the battery are controlled/scheduled with the help of the smart INDLs module, the smart DLs module, and the smart battery module respectively as per the instruction received from the SRMES.

Step 11: Update the changes if any such as changes in dead time intervals and extended tolerance limit of the INDLs through user interface module.

Step 12: Repeat Steps 7 to 11 until the user manually interrupts the SREMS.

3 Modeling of residential components

In this paper, a residential building with several household appliances along with the battery energy storage is considered for study. For simplicity, the modeling of all the household components is done for steady-state performance analysis, whereas the initial switching transients are not taken into account.

3.1 Modeling of ENDLs

As discussed in Section 2, the power consumption pattern of the ENDLs varies as per the consumer's interest. Further, controlling the operation of these loads may reduce the comfort of the user. Hence, the SREMS does not have any control on these loads. However, the SREMS has provision to give an alert message whenever the ENDLs demand exceeds the predefined limit. This would help the consumer to reduce the electricity bill by reducing the power consumption.

3.2 Modeling of INDLs

The power consumption pattern of the INDL is totally dependent upon the thermal dynamics of the surroundings. Once the user initializes an INDL, it compares the present room temperature with the consumer set temperature. For cooling the INDL (heating INDL), if the room temperature is above (below) the tolerance limit at a temperature set by the user, it starts to consume the rated power until the operating temperature reaches the temperature set. If the operating temperature is within tolerance limit, the INDL continues the previous interval operation. This process is repeated till the user manually disconnects the power supply of the INDL.

Let us consider that a residential building has a set of INDLs ($\mathbb{C}$) with user defined set of monitoring intervals ($\mathbb{Q}$). The status vector which expresses the operation (RUN/STANDBY) of an INDL c ($c \in \mathbb{C} \triangleq [1,2,...c,...,C]$) in each interval q ($q \in \mathbb{Q} \triangleq [1,2,...Q]$) is defined as

$$\boldsymbol{O}_c = [o_c^1, o_c^2, \cdots, o_c^q, \cdots, o_c^Q], \forall c \in \mathbb{C}, \tag{1}$$

where C is number of available INDLs and Q is the user defined number of non-deferrable load (NDL) intervals in a day,

$$Q = 24 \cdot \left(\frac{60}{A_{\text{NDL}}}\right).$$

Here, A_{NDL} is the duration of a non-deferrable load interval in minute. Considering different types of INDLs, if c is a cooling load, the status (o_c^q) of c during the interval q can be expressed as

$$o_c^q = \begin{cases} -1 & \text{if } c \text{ is not yet initialized} \\ 0 & \text{if } Hat_c^{q-1} < Hst_c \\ 1 & \text{if } Hat_c^{q-1} > Hst_c + \Delta Htl_c \\ o_c^{q-1} & \text{if } Hst_c \leqslant Hat_c^{q-1} \leqslant Hst_c + \Delta Htl_c \end{cases}. \tag{2}$$

If c is a heating load, it can be expressed as

$$o_c^q = \begin{cases} -1 & \text{if } c \text{ is not yet initialized} \\ 0 & \text{if } Hat_c^{q-1} > Hst_c \\ 1 & \text{if } Hat_c^{q-1} \leqslant \Delta Hst_c - \Delta Htl_c \\ o_c^{q-1} & \text{if } Hst_c - \Delta Htl_c \leqslant Hat_c^{q-1} \leqslant \Delta Hst_c \end{cases}, \tag{3}$$

where Hst_c and ΔHtl_c are the user set point temperature and maximum allowable tolerance limit of an INDL c respectively. The actual temperature at the end of interval $q-1$ is represented as Hat_c^{q-1}.

3.3 Modeling of DLs

The DLs are flexible to schedule and operate anywhere within the pre-fixed time span. The user has provision to fix the length of time span as per the required comfort and desire. Let the building be equipped with set of DLs ($\mathbb{D}$). The status (ON/OFF) of DL d over a day is expressed by the scheduling vector $\boldsymbol{L}_d$ which is defined as

$$\boldsymbol{L}_d = [l_d^1, l_d^2, ..., l_d^r, ..., l_d^R], \quad \forall d \in \mathbb{D}, \tag{4}$$

where R is the total number of deferrable load intervals in a day

$$R = 24 \cdot \left(\frac{60}{A_{\text{DL}}}\right).$$

Here, A_{DL} is the duration of each deferrable load interval in minute set by the consumer. Individual element of the scheduling vector l_d^r describes the status of the DL d during deferrable load interval r and is given as

$$l_d^r = \begin{cases} 0 \text{ if load } d \text{ is OFF} \\ 1 \text{ if load } d \text{ is ON} \end{cases}, \forall d \in \mathbb{D}\,;\; r = 1,2,...,R. \tag{5}$$

The SREMS receives the functional parameters of DLs from the user from the user interface module or directly from the DLs (if it has advanced communication features). This information includes the load initialization interval (α_d) in which the SREMS can add the load d into the scheduling process and dead time interval (σ_d) in which the task of the corresponding load d should be completed. The actual number of intervals required to complete the task (τ_d) can be either set by the user or computed by the DL if it possesses any artificial intelligence. For example, a smart cloth washer computes the τ_d by considering the weight of clothes put into it. In the same way, a well pump computes τ_d by sensing the present water level in the water tank. The necessary condition for the selection of the time span of operation is expressed as

$$\tau_d \leqslant \sigma_d - \alpha_d, \forall d \in \mathbb{D}. \tag{6}$$

As discussed in the architecture, some of the DLs (NPDLs) should RUN continuously once they are started. The SREMS distinguishes this kind of DL by considering its preemptive status which is updated by the user. The preemptive status of the deferrable load d is represented by ϕ_d and its value is assigned as

$$\phi_d = \begin{cases} 0 \text{ for interrptive loads (PDLs)} \\ 1 \text{ for non interruptive (NPDLs)} \end{cases}. \tag{7}$$

3.4 Modeling of battery

The controllable parameters while modeling the battery are the mode of operation (charging/floating/discharging) and the amount of power exchange. Further, the SREMS considers the battery as DL while charging, whereas during discharging it is considered to be an additional source. Let U be assumed to be the set of battery scheduling intervals. The operating vector which represents the mode of operation of the battery (charging (S_c^u), floating (S_f^u) and discharging (S_d^u)) in interval u ($u \in \mathbb{U} \triangleq [1,2,...,U]$), is defined as

$$\boldsymbol{S} = [\boldsymbol{S}^1, \boldsymbol{S}^2, \cdots, \boldsymbol{S}^u, \cdots, \boldsymbol{S}^U], \tag{8}$$

$$\boldsymbol{S}^u = [S_{\rm c}^u, S_{\rm f}^u, S_{\rm d}^u]. \tag{9}$$

The number of scheduling interval U in a day is obtained as $U=24\cdot\left(\frac{60}{A_{\rm BS}}\right)$. Here, the duration of battery scheduling interval $A_{\rm BS}$ is fixed by the user as suggested by the manufacturer. Each element of the operating vector in interval u is expressed as

$$\boldsymbol{S}^u = [S_{\rm c}^u, S_{\rm f}^u, S_{\rm d}^u] = \begin{cases} [1,0,0] & \text{if charging} \\ [0,1,0] & \text{if floating} \\ [0,0,1] & \text{if discharging} \end{cases}. \tag{10}$$

During starting of each battery scheduling interval (u), the available SOC of the battery (X^u) is obtained by using Eq. (11) [24]

$$X^u = \left(\mathrm{Cap}(u-1)+\zeta_{\rm Bat}\left(\frac{P_{\rm S}^u}{V_{\rm Bus}}\right)\left(\frac{A_{\rm BS}}{60}\right)\right)\cdot\left(\frac{1}{M_{\rm cap}}\right), \tag{11}$$

where $\mathrm{Cap}(u-1)$ is the battery capacity in Ah during starting of interval $u-1$, $\zeta_{\rm Bat}$ is the round trip efficiency of the battery, $V_{\rm Bus}$ is the DC bus voltage in V, and $M_{\rm cap}$ is the maximum Ah capacity of the battery. The battery storage power for interval u, $P_{\rm S}^u$ can be obtained using Eq. (12)

$$P_{\rm S}^u = (1-S_{\rm f}^u)(S_{\rm c}^u\cdot P_{\rm SC}^u - S_{\rm d}^u\cdot P_{\rm SD}^u), \tag{12}$$

where the subscript S stands for battery storage, $P_{\rm SC}^u$ is the battery storage charging power and $P_{\rm SD}^u$ is the battery storage discharging power of the battery, the subscript SC and SD stand for battery storage charging and battery storage discharging, respectively.

4 Scheduling of different components

The objective of the SREMS proposed is to reduce the total electricity bill to be paid to the utility without disturbing the consumer's comfort and desire. To achieve this, the SREMS shifts the operation of the DLs from peak intervals when the energy cost is high to non-peak or mid-peak intervals when the energy cost is comparatively less. Further, the SREMS maintains the total demand under CCL to avoid excess payment. The full time horizon of the SREMS is divided into different types of intervals, namely the NDLs, the DLs, battery scheduling, and pricing intervals. The duration of non-deferrable load interval ($A_{\rm NDL}$) is decided by the users based on their own interest. Generally, $A_{\rm NDL}$ is preferred to have a short time duration in order to appropriately consider the practical variations in the demand pattern of the NDLs. The power demand by the NDLs (ENDLs and INDLs) is assumed to be constant for a given non-deferrable load interval q. The duration of deferrable load intervals ($A_{\rm DL}$) is defined by the consumer with due considerations to the operational constraints of the DLs. The operation of the DLs is non-interruptible in the given deferrable load interval (r) if the status of the DLs is ON at the beginning of the interval.

The selection of the duration of the battery scheduling interval ($A_{\rm BS}$) mainly depends upon the direction given by the manufacturer on the continuous operation of battery. During a particular battery scheduling interval (u), the SREMS fixes the mode of operation of battery and the amount of power exchange by it. Finally, the pricing interval duration ($A_{\rm P}$) is fixed by the utility. The electricity price remains constant during a pricing interval. From the present and history data, the electricity price can be predicted for the future intervals. Appreciable performance of the SREMS would be anticipated when the duration of various intervals satisfies

$$A_{\rm P} \geqslant A_{\rm DL} \geqslant A_{\rm BS} \geqslant A_{\rm NDL}. \tag{13}$$

Since the operation of the ENDLs is merely dependent upon the consumer availability, comfort and desire, the SREMS cannot control these loads. However, the expected total power required for the operation of all ENDLs during the present and future intervals is considered in the scheduling process to maintain the total demand under CCL in every interval. Succinctly, the SREMS provides the optimal values of decision variables o_c^q, l_d^r, $\boldsymbol{S}^u$, $P_{\rm SC}^u$, and $P_{\rm SD}^u$ for all the intervals so as to reduce the electricity bill of the consumer. The basic steps involved in the scheduling of household components by SREMS are presented as a flowchart in Fig. 2.

4.1 Scheduling of INDLs

As the INDLs are mainly luxurious loads, the time scheduling of them would utterly affect the comfort of the consumer. However, the SREMS can interrupt the operation of these loads if the user is more concerned about the electricity bill. To achieve this, the consumer has to extend the tolerance limit defined by the manufacturer. If the total demand exceeds the CCL, the SREMS can interrupt the operation of the INDL till the present operating temperature reaches the user defined extended tolerance limit (ΔHel_c). In the case that more numbers of the INDLs are initialized simultaneously, the SREMS controls them by considering the priority of each load. If c is a cooling load, the priority of an INDL c in interval q, F_c^q is determined as

$$F_c^q = \begin{cases} 0 & \begin{cases} \text{if INDL } c \text{ is not yet initialized} \\ \text{else if } Hat_c^{q-1} < Hst_c \end{cases} \\ 1-\Delta F_c^q & \text{otherwise} \end{cases}, \tag{14}$$

$$\Delta F_c^q = \frac{Hst_c + \Delta Htl_c + \Delta Hel_c - Hat_c^q}{\Delta Htl_c + \Delta Hel_c}. \tag{15}$$

If c is a heating load, it is determined as

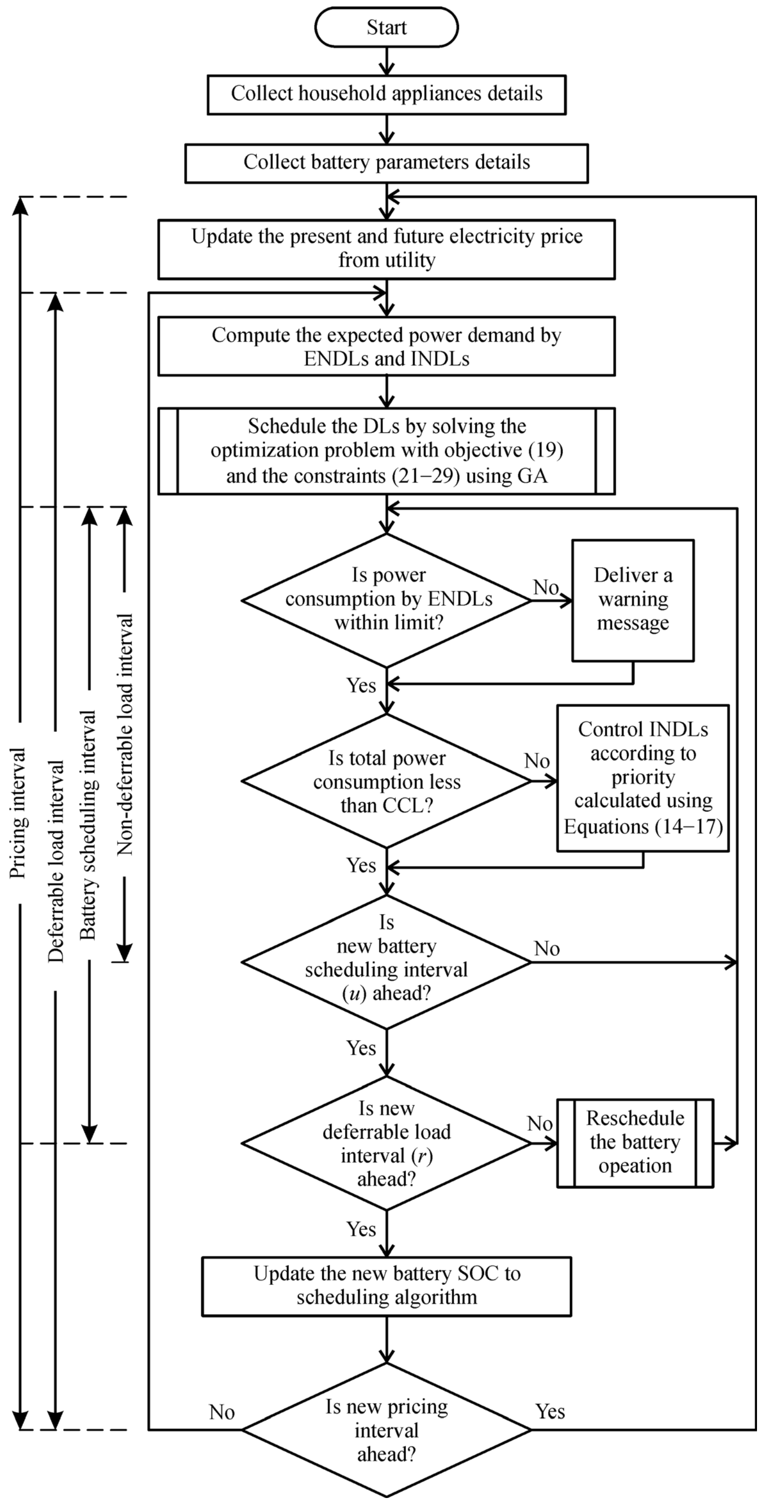

Fig. 2 Flowchart of proposed SREMS

$$F_c^q = \begin{cases} 0 & \begin{cases} \text{if INDL } c \text{ is not yet initialized} \\ \text{else if } Hat_c^{q-1} > Hst_c \end{cases}, \\ 1 - \Delta F_c^q & \text{otherwise} \end{cases} \tag{16}$$

$$\Delta F_c^q = \frac{Hat_c^q - (Hst_c - \Delta Htl_c - \Delta Hel_c)}{\Delta Htl_c + \Delta Hel_c}. \tag{17}$$

The SREMS decides to operate the INDLs having a priority greater than or equal to 1. To satisfy the CCL constraint, the rest of the INDLs are operated in the order of high to low priority. However, the SREMS delays the operation of low priority loads to subsequent intervals when the total demand exceeds the CCL.

4.2 Scheduling of DLs

Since the operation of DLs is flexible with the utility parameters (electricity price and CCL), the SREMS optimally schedules the DLs to achieve reduction in the total electricity bill. This scenario is modeled as an optimization problem with the objective function as minimization of the total electricity bill subjected to various operational constraints. To account the real time modifications, the SREMS does the scheduling process between the present deferrable load interval and the maximum dead time interval (r_{md}) of all initialized and not completed DLs. Hence, the set of deferrable load intervals which is used for the optimization process varies dynamically in every interval. This dynamic set ($\mathbb{I}$) with the present operating interval (r) is expressed in

$$\mathbb{I} = [r, r+1, ..., r_{\mathrm{md}}]. \tag{18}$$

The objective function of the optimization problem proposed is given in

$$\min\left(\sum_i E_{\mathrm{T}}^i \cdot \Gamma^i\right), \quad \forall i \in \mathbb{I}, \tag{19}$$

$$E_{\mathrm{T}}^i = \left(P_{\mathrm{ENDL}}^i + P_{\mathrm{NDL}}^i + P_{\mathrm{DL}}^i + P_{\mathrm{S}}^i\right) \cdot \left(\frac{A_{\mathrm{DL}}}{60}\right), \tag{20}$$

where i is an element of the dynamic set $\mathbb{I}$ and the total energy consumption during interval i is E_{T}^i and the utility electricity price for interval i is Γ^i. During optimization, the SREMS reserves the expected power (P_{ENDL}^i and P_{NDL}^i) for the operation of the NDLs (ENDLs and INDLs) in the upcoming intervals. P_{DL}^i is the total power demand by DLs, which includes the reserved power for the operation of the NPDLs (which are started in previous intervals) and the required power for the scheduled DLs in interval i, and P_{S}^i is the scheduled battery power in interval i. The constraints involved in the optimization process are expressed in the subsequent subsections.

4.2.1 Load scheduling constraint

Any DL should be scheduled only during the user predefined time span $[\alpha_d, \sigma_d]$. Therefore, if the deferrable load interval r does not exist in the predefined time span, the operating status of the DL d during interval r (l_d^r) should be zero. This is a hard constraint and expressed as

$$\begin{aligned} l_d^r = 0;\ r < \alpha_d,\ \forall d \in \mathbb{D} \\ l_d^r = 0;\ r > \sigma_d,\ \forall d \in \mathbb{D} \end{aligned}. \tag{21}$$

4.2.2 Number of intervals constraint

As discussed in Section 2, the DLs are smart enough to find the number of intervals required to complete the task assigned. The SREMS should schedule the DLs only for the number of intervals. This hard constraint is given in Eq. (22).

$$\sum_{j=r}^{\sigma_d} l_d^j = \gamma_d^j,\ \forall d \in \mathbb{D}, \tag{22}$$

where γ_d^r is the number of intervals needed to complete the task from interval r.

4.2.3 Interruption constraint

The NPDLs should be operated continuously once they begin their assigned task. This is formulated as a hard constraint and given in Eq. (23):

$$\sum_{\in=0}^{\varphi-1} \prod_{Q=\alpha_d+\in}^{\alpha_d+\tau_d+\in-1} l_d^Q \phi_d = \phi_d, \tag{23}$$

$$\varphi = \sigma_d - \alpha_d - \tau_d + 2. \tag{24}$$

4.2.4 Consumer consumption constraint

To reduce the total electricity bill, the total demand of the consumer at any interval r should be maintained within CCL (P_{CCL}^r) assigned by the utility. Whenever the consumer consumes beyond CCL, they are penalized with a high cost by the utility. Hence, the SREMS should consider the expected demand of the NDLs (ENDLs and INDLs) for future intervals while scheduling the DLs. Further, the SREMS should schedule the battery operation in such a way that the battery supports the demand during peak intervals. Always trying to keep the power demand under CCL may occasionally affect the comfort of the consumer. Hence, this constraint is considered as a soft constraint which is expressed in Eq. (25).

$$\begin{cases} P_{\mathrm{ENDLs}}^r + P_{\mathrm{NDLs}}^r + P_{\mathrm{DLs}}^r + P_{\mathrm{S}}^r \leqslant P_{\mathrm{CCL}}^r \\ \dfrac{1}{\nu^{r+1}}\left(P_{\mathrm{DLs}}^{r+1} + P_{\mathrm{S}}^{r+1}\right) \leqslant P_{\mathrm{CCL}}^{r+1} \\ \vdots \\ \dfrac{1}{\nu^{r_{\mathrm{md}}}}\left(P_{\mathrm{DLs}}^{r_{\mathrm{md}}} + P_{\mathrm{S}}^{r_{\mathrm{md}}}\right) \leqslant P_{\mathrm{CCL}}^{r_{\mathrm{md}}} \end{cases}, \tag{25}$$

where ν^r is the user defined factor to reserve power for the operation of NDLs in interval r. The expected demand of the NDLs is either computed from the history of data or directly obtained from the user. Either avoiding the consideration of expected demand of the NDLs for future intervals or assuming the same expected demand for the NDLs during all deferrable load intervals leads the SREMS to scheduling all the DLs during non-peak or mid peak intervals, which may violate the consumer consumption constraint. Hence, the reservation factor is introduced in the constraint. This factor varies in the range of [0, 1].

4.2.5 Battery constraints

In each deferrable load interval, the SREMS has to schedule the battery operation in any one of the following modes: charging, discharging, and floating. This is formulated as a hard constraint and given in Eq. (26).

$$\boldsymbol{S}^r = S_{\mathrm{c}}^r + S_{\mathrm{f}}^r + S_{\mathrm{d}}^r = 1, \tag{26}$$

where $\boldsymbol{S}^r$ is the scheduled operating vector which represents the mode of operation of the battery (charging S_{c}^r, floating S_{f}^r and discharging S_{d}^r) in a deferrable load interval r.

The variable parameters of the battery such as SOC, charging power, and discharging power should be maintained in between their maximum and minimum limits for preserving the life of the battery. These hard constraints are formulated as

$$X_{\min} \leqslant X^r \leqslant X_{\max}, \tag{27}$$

$$P_{\mathrm{BCmin}} \leqslant P_{\mathrm{SC}}^r \leqslant P_{\mathrm{BCmax}}, \tag{28}$$

$$P_{\mathrm{BDmin}} \leqslant P_{\mathrm{SD}}^r \leqslant P_{\mathrm{BDmax}}, \tag{29}$$

where $[X_{\min}, X_{\max}]$, $[P_{\mathrm{BCmin}}, P_{\mathrm{BCmax}}]$ and $[P_{\mathrm{BDmin}}, P_{\mathrm{BDmax}}]$ are the minimum and maximum limits of the battery SOC, charging power, and discharging power respectively. The SOC of the battery at any deferrable load interval r (X^r) is calculated at the starting of the corresponding interval. P_{SC}^r and P_{SD}^r are the scheduled charging and discharging power of the battery for interval r respectively.

The optimization problem formulated with the objective function (Eq. (19)) and subject to various hard and soft constraints (Eqs. (21–29)) is solved using the genetic algorithm (GA). The optimal parameters (l_d^r, $\boldsymbol{S}^r$,P_{SC}^r, and P_{SD}^r) which are obtained as the result of the optimization problem proposed are used by the SREMS to achieve reduction in total electricity bill. The steps involved in the optimization process are briefed in Algorithm-1 (optimal scheduling of DLs and battery using GA) as below.

Step 1: Start the optimization process with variables (l_d^r, $\boldsymbol{S}^r$, P_{SC}^r and P_{SD}^r).

Step 2: Define the population size and maximum number of iterations for the GA.

Step 3: Initialize the iteration count as 1.

Step 4: Randomly assign the initial population.

Step 5: Set the population count as 1.

Step 6: Compute the objective function and check for constraint satisfaction.

Step 7: Pick the next population and repeat the previous step until all population are considered.

Step 8: From the present iteration, formulate the population set for the next iteration using GA operators (crossover and mutation).

Step 9: Repeat Steps 5–8 till the iteration count reaches the maximum value.

Step 10: Export the optimal schedule of the DLs and the battery which satisfies all the constraints with the minimum electricity bill.

4.3 Scheduling of battery

If the duration of battery scheduling and deferrable load interval is the same, the battery follows the mode of operation and the amount of power transfer dictated by the scheduling algorithm. If the duration of these intervals is different, rescheduling of the battery within a deferrable load interval may increase the savings in the electricity bill. This rescheduling should be done with due consideration to the dynamics in the operation of the NDLs and utility parameters because the power demanded by the NDLs are not fixed for the entire deferrable load interval.

For example, during a particular deferrable load interval, assume that the scheduling algorithm decides the mode of operation of the battery as charging, but due to the increase in the number of persons, the total demand by the NDLs increases. In this situation, if the battery follows the charging mode operation for the entire deferrable load interval, the total demand of the consumer may exceed the CCL and the total electricity bill may increase. Hence, the mode of operation of the battery may be rescheduled. However, rescheduling the battery operation in every non-deferrable load interval badly affects the life of the battery. To save the life of the battery, the SREMS reschedules the battery operation only in every battery scheduling interval u while considering the total demand P_E^u and the SOC limitation.

Here, P_E^u is the total household demand excluding the scheduled battery power exchange during interval u. As a part of the flowchart depicting the functioning of the SREMS proposed as presented in Fig. 2, the steps involved in the rescheduling of the battery operation is given in Fig. 3.

5 Case study

The framework proposed is validated through a case study by analyzing the possible reduction in the electricity bill to be paid to the utility by a residential consumer. A residential building located at the National Institute of Technology in Tiruchirappalli, India is considered for the

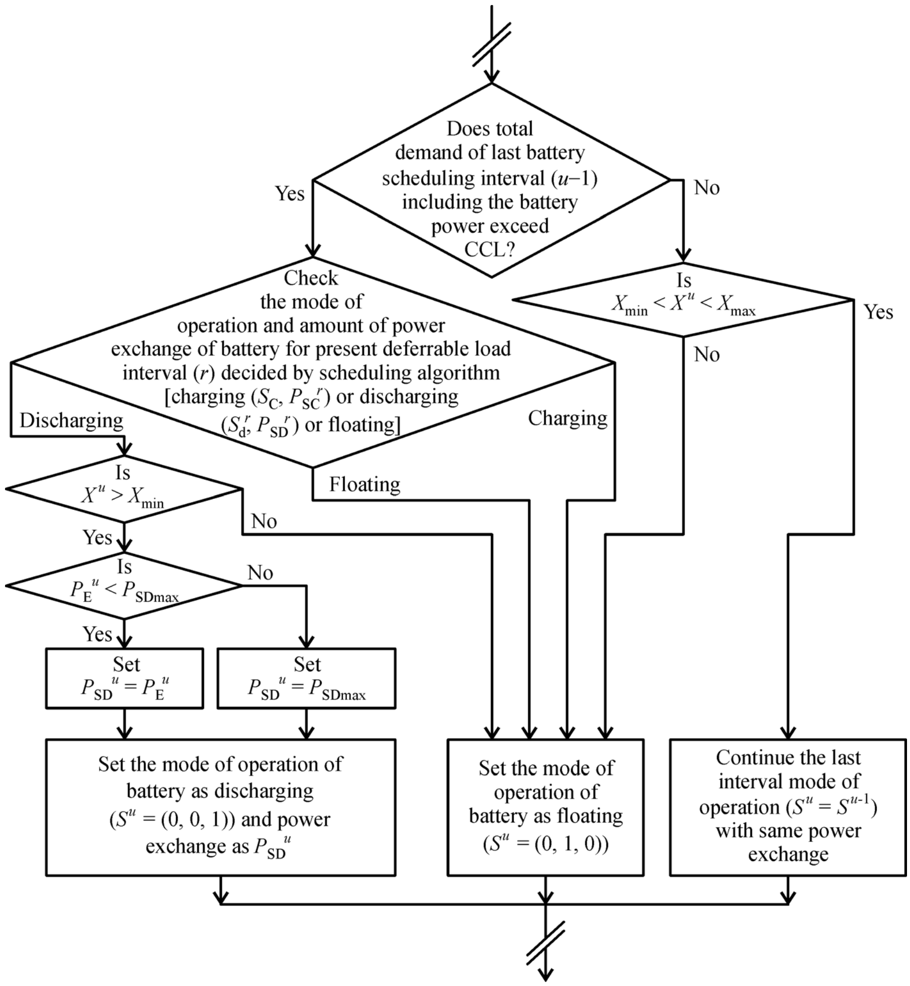

Fig. 3 Rescheduling the battery operation

case study.

5.1 Study environment

The details along with the power rating of the ENDLs, INDLs and DLs in the residential building considered for the case study are given in Tables 1, 2 and 3 respectively.

Further, the residential building is supported with an energy storage device. It is assumed that the lead acid type of the battery is used as the energy storage device. This type of battery is commonly preferred by residential consumers because of its operational advantages (relatively low price, low investment cost, high availability, reasonable performance, and long life cycle) [10]. The battery parameters are listed in Table 4.

The duration of intervals are chosen in such a way that the comfort of the user as well as the operational constraints is not disturbed. The details of the duration of intervals are tabulated in Table 5. To attain maximum benefits, the necessary duration relationship ($A_P \geqslant A_{DL} \geqslant A_{BS} \geqslant A_{NDL}$) is maintained, while selecting the duration of various intervals.

Table 1 ENDLs

S. No	Load	Power rating/kW
1	Fan	0.10
2	Fluorescent lamp	0.04
3	Compact fluorescent lamp (CFL)	0.02
4	Television (TV)	0.25
5	Mobile/laptop charging	0.05

Table 2 INDLs

S. No	Load	Power rating/kW
1	AC-1	1.5
2	Water heater	2.0
3	Refrigerator	0.5
4	AC-2	1.0

The utility defined CCL is presumed as 4 kW which is

Table 3 DLs

S. No	Load	Power rating/kW	Interruptive status
1	Cloth washer	0.8	1
2	Cloth dryer	2.7	1
3	Dish washer	2.1	0
4	Well pump	1.5	0
5	PHEV charging	2.3	0
6	Grinder	0.5	1

Table 4 Battery specifications

S. No	Parameter	Rating
1	Capacity	200 Ah
2	Voltage	12V
3	Charging efficiency	85%
4	Discharging efficiency	95%
5	SOC limit	(30–90)%
6	Charging current limit	(5–20)% of rated capacity
7	Discharging current limit	(0–20)% of rated capacity

Table 5 Duration of intervals

S. No	Interval	Duration/min
1	Non-deferrable load	1
2	Battery scheduling	5
3	Deferrable load	15
4	Pricing	60

anticipated to be constant for all pricing intervals (peak, mid-peak, and non-peak intervals) in a day. The utility penalization for consuming more than CCL is considered to be 2.5 times of base payment. The optimization problem involved in the SREMS scheduling process is solved by using GA with a maximum iteration of 150 and a population size of 100. The SREMS framework proposed is developed in Matlab. References [25,26] reported various energy cost prediction techniques for future intervals. However, this particular study assumes that the utility provides the electricity price for the present and future intervals through the smart meter.

5.2 Results and discussion

The results of this case study are presented and compared with the daily and annual electricity bill obtained without the SREMS proposed and the energy storage device. It is found that the SREMS reduces the electricity bill on the day of simulation from 200.94 cents to 163.57 cents, which results in a 18.32% reduction in daily electricity bill.

The maximum demand of the building for all deferrable load intervals is obtained and exhibited in Fig. 4. It can be observed that the SREMS maintains the demand within CCL in almost all deferrable load intervals. The duration of the total demand exceeding CCL in a day is reduced from 219 min to 95 min and the energy consumption with excess payment is also reduced from 5.43 kWh to 0.86 kWh. For better comparison, the variations in the average demand of different categories of household components over the duration of deferrable load interval in both the methods (without and with SREMS) are demonstrated in Fig. 5.

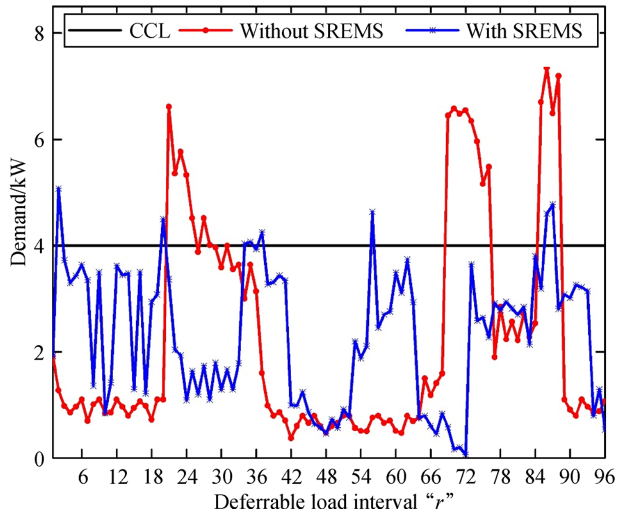

Fig. 4 Comparison of maximum demand

To analyze the effectiveness of the SREMS proposed, the simulation is further extended to a period of one year. The duration of all intervals (A_{NDL}, A_{BS}, A_{DL}, and A_{P}) are considered as one hour to show the results for better clarity. The total electricity bill of the residential building considered is reduced from \$2336.84 to \$1824.72, which confirms that there is a 21.92% reduction in the annual electricity bill. The hourly demand variation of different categories of household loads for a particular week in different climatic seasons (month of January, May and September) without and with the SREMS are depicted in Figs. 6(a) and 6(b) respectively. The set of the daily electricity bill by all the components during different months (January, May and September) without and with the SREMS are plotted in Figs. 7(a) and 7(b) respectively.

The results obtained from this case study confirm that the SREMS reduces the electricity bill by properly time scheduling the DLs and the battery while considering the dynamics in the operation of the NDLs and utility parameters. The SREMS schedules the battery to a charging mode whenever the electricity price is comparatively less (non-peak intervals). However, the battery is set to be in a discharging mode when the price is high (peak intervals). Succinctly, the SREMS maintains the total household demand within CCL by properly adjusting the battery power exchange during its different modes of

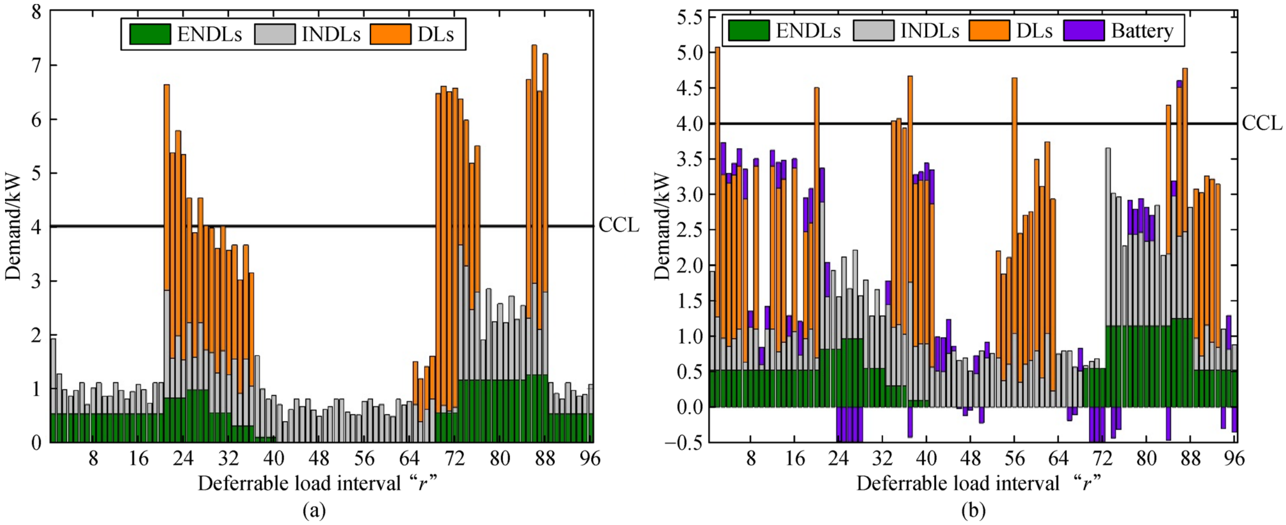

Fig. 5 Comparison of averaged demand variation
(a) Without SREMS; (b) with SREMS

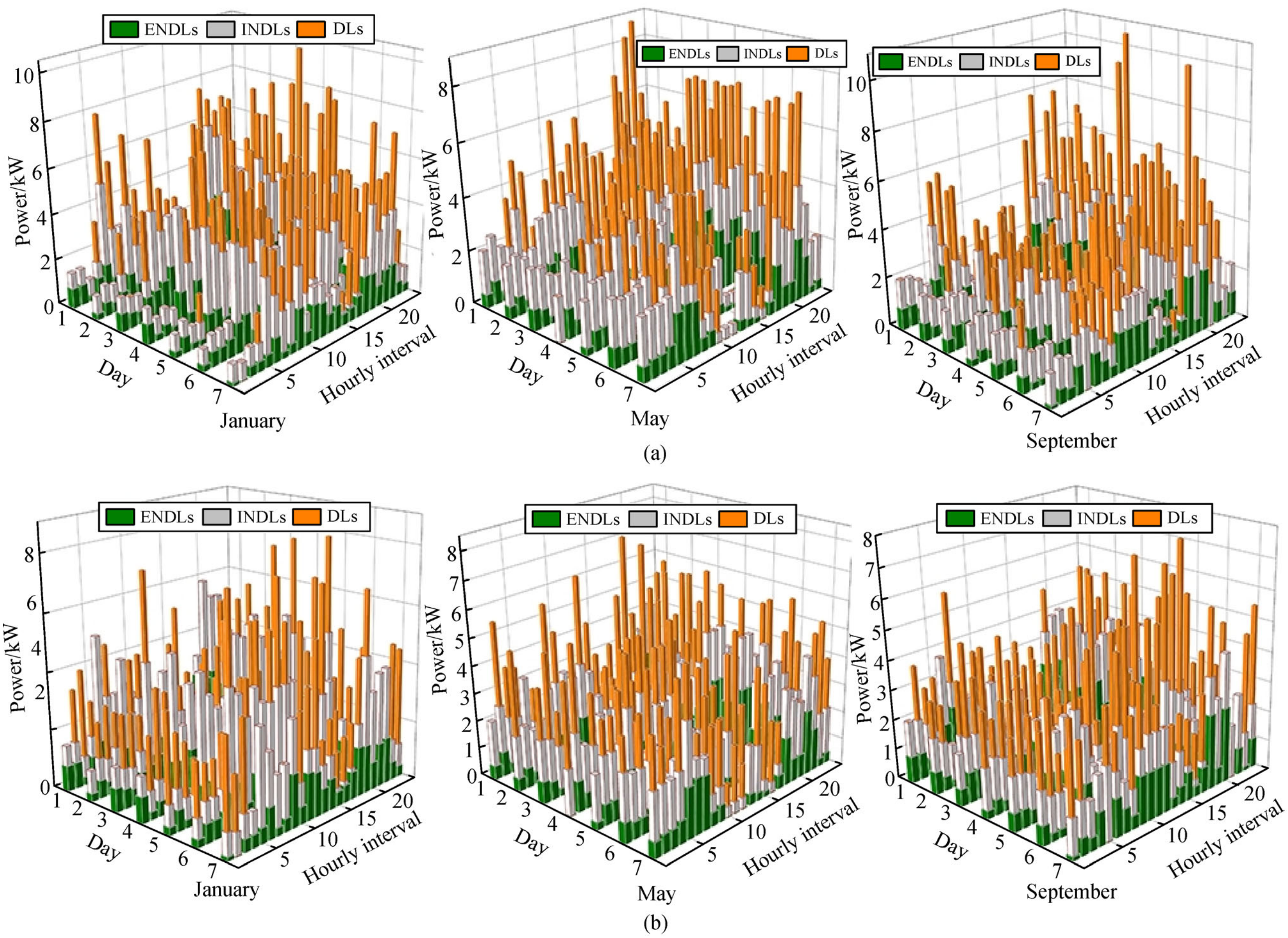

Fig. 6 Demand variation over a week in different months
(a) Without SREMS (consumer behavior); (b) with SREMS

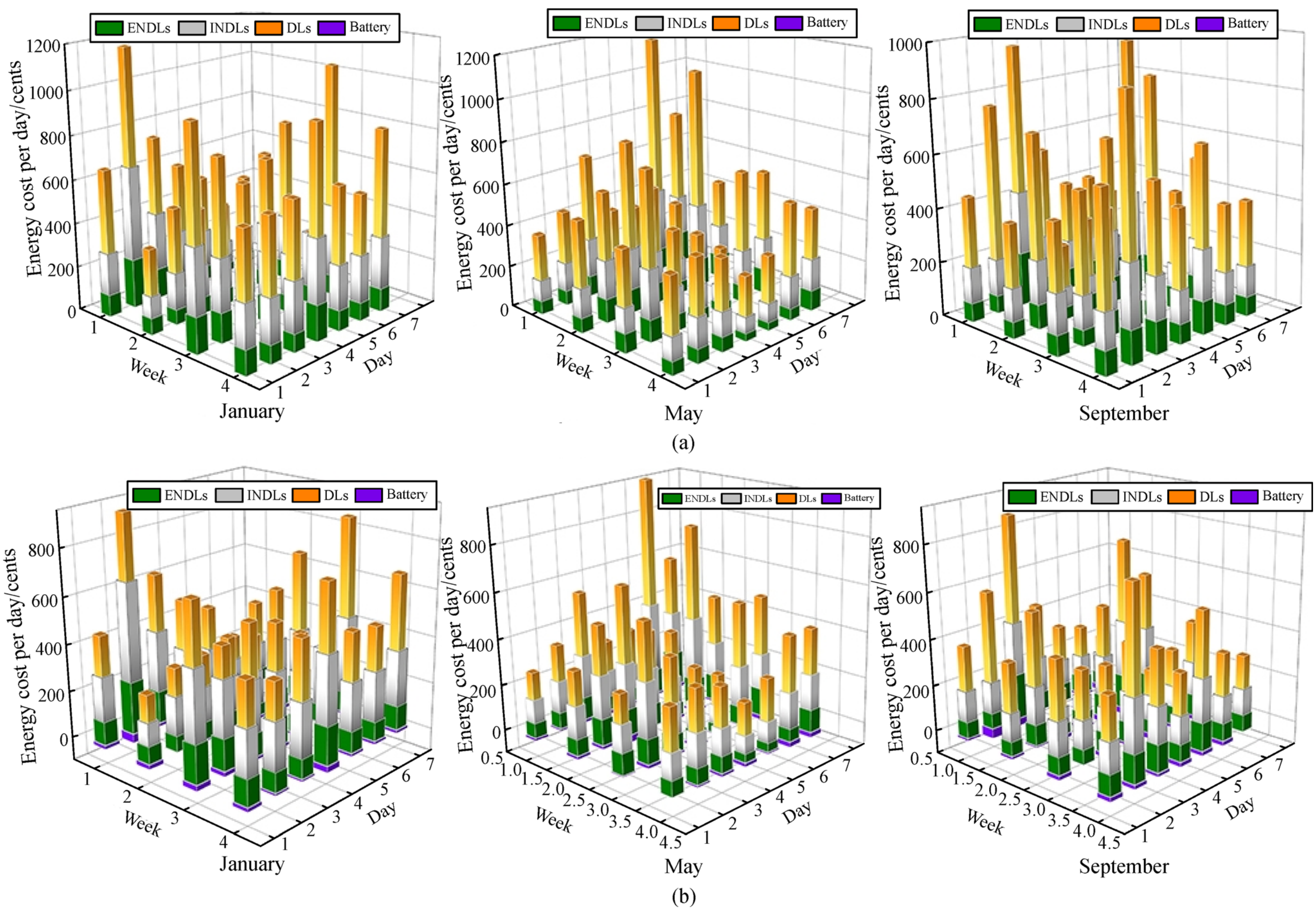

Fig. 7 Components of energy cost per day in different months
(a) Without SREMS; (b) with SREMS

operations. To examine the performance of the SREMS proposed with the battery, the simulation study is extended to different battery capacities. The battery SOC is considered to be in its minimum limit at the starting of the study and the residential load pattern is assumed to be the same for all the days under study. The battery SOC variations for different battery ratings with CCL 2 kW and 4 kW are computed and presented in Figs. 8 and 9 respectively. From Figs. 8 and 9, it is very clearly observed that the algorithm proposed leads to a similar charging and discharging cycle for different ratings of the battery. Further, the maximum depth of discharge observed is around 25% only, which helps in preserving the battery life.

6 Conclusions

In the present scenario, utilities are encouraging the residential consumers to actively participate in the electricity market through DSM programs. Consumers are approaching various DR techniques in order to gain more benefit from the utility. In this paper, a SREMS-based DR technique is proposed for residential consumers to reduce the total electricity bill by properly time scheduling the DLs with due consideration to the operational dynamics of the NDLs and the utility parameters such as CCL and energy price. The mode of operation of the battery and power exchange from the battery is also effectively scheduled along with the DLs in order to maintain the total demand within utility defined CCL so as to avoid excess payment. The framework proposed is validated with the test data obtained from a residential building located on the campus of National Institute of Technology in Tiruchirappalli, India. The results confirm that the SREMS proposed considerably reduces the electricity bill. Further the charging and discharging cycles of the battery are effectively scheduled by the SREMS, for preserving the battery life. The results obtained from the SOC analysis while considering the different battery rating and CCL prove the effectiveness of the SREMS proposed in properly scheduling the battery.

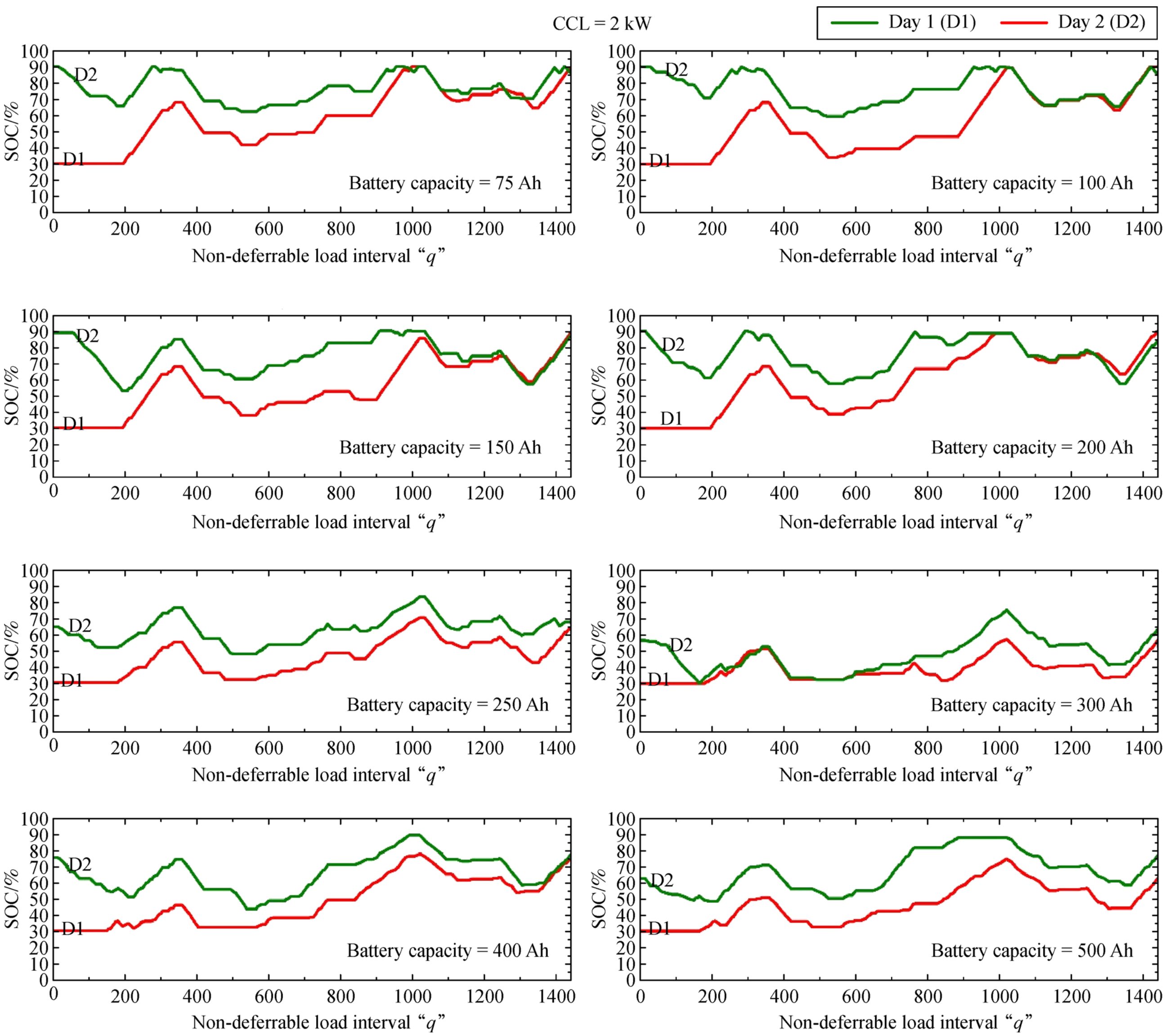

Fig. 8 Battery SOC variation for different battery ratings at CCL = 2 kW

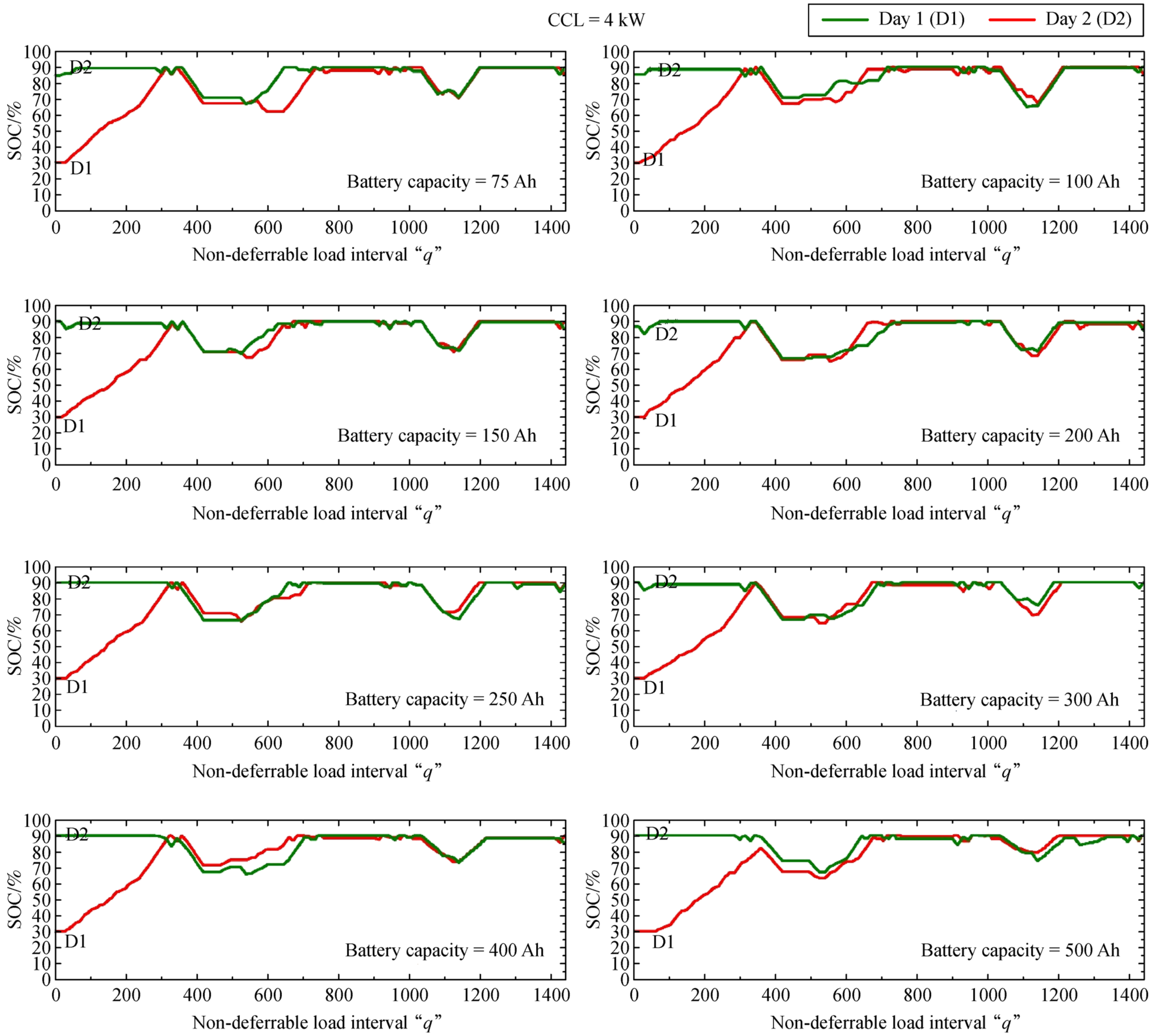

Fig. 9 Battery SOC variation for different battery ratings at CCL = 4 kW

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