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Optimized Cost of Energy by a Home Energy Management System Employing Dynamic Power Import Limit Strategy: A Case study Approach

*V. D. Juyal *, S. Kakran*

Electrical engineering department, National Institute of Technology Kurukshetra, India

Abstract— *Nowadays, the centralized power system is changing to a distributed system, and various energy management systems are being installed for efficient functioning. Load side management is a vital aspect of the energy management of the power network. As residential demand is growing at a high rate, domestic customers play a crucial role in the successful implementation of demand response (DR) programs. This paper considers a single customer having a home energy management system (HEMS) for thermostatic and non-thermostatic characteristics-based appliances, photovoltaic panels, an electric vehicle, and a battery energy storage system. The effect of various DR strategies has been discussed. A mixed-integer linear programming-based model of a HEMS is modulated and solved to minimize the electricity consumption cost by employing a real-time price-based DR program using dynamic power import limits. An incentive-based DR program is considered for reducing the energy demand and maintaining the energy balance during peak hours, and peak pricing-based dynamic power import limiting DR programs are included for load shaping. The effect of load shaping on the peak to average ratio is also discussed in different scenarios. Finally, the total electricity price is calculated and analyzed by considering other test cases based on the inclusion/rejection of the mentioned DR programs.*

Keywords—Demand response, Home energy management, Smart household, Electric vehicle, Battery-energy storage system, Dynamic power import limit.

Time interval

NOMENCLATURE

Parameters

Δt

C_a The thermal capacity of air (KJ/Kg°C)

f_{PV} Factor to include the effect of dust

M_a Mass of air (Kg)

R_{eq} Equivalent thermal resistance (h.°C/KJ)

Z^{AC} Rated power of AC (kW)

β Coefficient of performance

θ_h^{CW} Inlet cold water temperature (°C)

$\theta^{HWmx.}$/ $\theta^{HWmn.}$ The maximum/minimum value of hot water temperature (°C)

Spt_h The set-point of AC temperature (°C)

ηch^{EV} / ηd^{EV} The EV's charging and discharging efficiency

∂_h^{buy} The price of electricity supplied by the grid (cents/kWh)

$H^{f\ ch}$/ $H^{f\ dis}$ Timeslot when the electric vehicle should be completely charged/discharged

$SE^{EV\ ini}$ The initial state of energy of the EV (kWh)

$SE^{EV\ mx}$/$SE^{EV.mn.}$ The EV's Maximum/minimum permitted state of energy (kWh)

Z_h^{MR} Energy demand of must-run appliances (kW)

z_h^{mx} The consumer's maximum load reduction at hour h

$Z_h^{PV.gen}$ Energy extracted from the PV (kW)

Variables

θ_h^{HW} The temperature of hot water (°C)

θ_h^{r} Room temperature (°C)

Z_h^{EWH} Energy consumed by EWH (kW)

Z_h^{ex} Extra grid energy purchased (kWh)

m_h^{EV} If there is EV charging during period h, the binary variable is 1; otherwise, it is 0.

m_h^{EWH} If EWH is operational, the binary variable is 1; otherwise, it is 0.

SE_h^{EV} The EV's State of energy (kWh)

$Z_h^{EV\ ch}$ The EV's Charging power at slot h (kWh)

$Z_h^{EV\ dis}$ The EV's Discharging power at slot h (kWh)

Z_h^{gr} Grid-supplied energy (kWh)

N The total number of schedules that can be used appliance 'a' of type-2

1. INTRODUCTION

Energy demand is increasing day by day due to the population and vigorously rising living standards of consumers. Authors [1] expected that energy demand would grow up to 30% more than the current value by 2040, and residential energy demand will also rise significantly in the future [2]. Due to the diminishing traditional fuels, the world is moving toward renewable energy resources [3]. It has been determined that only solar photovoltaics will contribute up to 20% in 2030 and up to 30% in 2050. According to the IEA report 2020, renewable is contributing nearly 28% of the global energy demand [4]. Many distributed energy resources (DERs) of small and medium power generators are being installed in the distribution sector. That's why managing and scheduling the available energy resources is imperative. The inclusion of DERs and increased power demand cause many problems for the utility as well as customers. Smart grid technology is proved to be a

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*Corresponding author:
E-mail: vikasdeep.juyal@gmail.com (V. D. Juyal)
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solution to many of these problems [5]. Energy scheduling at the load end can save the power system from stress during the peak demand hours [6]. Here, demand-side management (DSM) comes into the role.

The demand response (DR) program is a part of DSM and is the key to motivating consumers to participate in the energy management system [7]. It is the most effective tool for getting a smoother load curve, reducing cost, and enhancing the power system reliability [8]. By enabling communication with the customers, DR tries to match the demand and supply in a power network. This power balancing reduces capital costs by minimizing the need for extra generators and transmission lines [9]. In the residential loads, appliances like air conditioners (AC) and electric water heaters (EWH) are high-power appliances that also affect consumers' comfort levels. Scheduling of such appliances can change the load curve significantly [10], and hence it is necessary to include such appliances in the DR program at the residential level. In this era of development, smart homes are in focus, which are employed by loads like electric vehicles (EV) [11] as well as distributed generators like solar photovoltaics (PV), wind generators [12], and storage units like battery energy storage systems (BESS). With these smart home energy management, DR programs have the large potential to change the load curve significantly [13].

The authors [5] provided a detailed survey of DR programs, their mathematical models, issues, approaches, and DR programs' future extensions. Real-time pricing (RTP) is primarily regarded as one of the most effective and efficient price-based DR programs, according to a discussion of several incentive & price-based DR solutions. Mathematical models based on utility and cost functions have also been discussed. In [14], the authors provided a detailed review of residential, commercial, and industrial DR programs. Because of the importance of reliability management in industrial operations, industrial loads may be more challenging to apply DR than residential loads. The authors in [15] proposed a DR strategy for residential thermal appliances. The main focus was on the comfort level of the customer. The presented approach adjusted the temperature set-point of AC thermostats to reduce average discomfort among DR program participants while also meeting the utility's DR event requirements. In [16], the AC and air ventilation systems are considered, and the problem is optimized for electricity cost reduction. The study presented a decoupled DR technique and an interdisciplinary mechanism that combines machine learning, optimization, and data structure design to design and build the DR and HEMS. In [17], the authors took the thermal zone-stratified model of EWH based on the energy balance phenomenon. The control strategy was based on dynamic programming and the classification of power consumption profiles, and the modeling was done to reduce energy demand and increase user satisfaction. In [18], BESS has been included to get the optimum solution for a home energy management system (HEMS) using adaptive dynamic programming to control and coordinate several batteries. The authors [19] considered both energy storage system and EV with the EV to home (V2H) and EV to grid (V2G) modes in the energy management system (EMS) with a peak power limiting strategy.

The above-discussed papers contribute significantly to smart grid applications and DR strategies. Still, many research papers did not include the applications like the V2H/V2G operating mode of EV and BESS. Some papers focused on a particular type of appliance [17], [20] and didn't include all kinds. The authors in [15–18] concentrated on modeling a single appliance. However, they neglected to consider loads like electric vehicles (EVs), which might be employed as an energy storage system after charging and result in a decrease in the amount of power used. Shiftable and controllable appliances were not included in [19], which could support the energy management of a smart home. For an islanded microgrid, linear programming has been used to design and solve the optimization issue for the most cost-effective utilization of production and storage units [21]. It is recognized that diesel generator units' efficiency varies depending on the production level. Plans for DSM have been offered in response to this issue, including the issue of load uncertainty.

An IoT-based large energy management system has been proposed by [22] for big data of 1 million residents employing smart meters. The generated data from one million meters was stored in a distributed format using a 4-node cluster, and parallel processing was carried out across nodes acting as master and slave nodes. The suggested solution has the ability to visualize customer behaviour at each level and is scalable for a big area. The authors of [23] developed a multiobjective model for reducing cost and peak demand in a residential area by incorporating customer satisfaction. The authors [24] proposed a realistic wind power generation scheduling on the utility side. Still, they didn't include any uncertainty on the demand side, and the customer's comfort level was also not considered in the study. In [22] & [23], the authors used the time of use (ToU) tariff for optimization, and [24] presented two-stage programming for scheduling the DR options in the real-time market & day-ahead market.

Different evolutionary computational tools like a genetic algorithm (GA) [25], particle swarm optimization (PSO) [26], whale optimization algorithm [27], and games theory [28] have also been used by different authors in various research papers for scheduling of HEMS. In the paper [29], various computational tools have been discussed and compared regarding computation time, complexity, and other factors. A fuzzy-based multiobjective model is presented by [30] considering the uncertainty brought on by energy generation from renewable sources and uncertain consumption by customers. The size and location of DERs, capacitors and interruptible loads have also been considered simultaneously. Heuristic computational techniques have been widely used in various recent research, which may take less time to calculate but are more computationally complicated than mathematical tools and tend to locate local minima rather than global minima. In [31], the authors considered various constraints for user satisfaction and power balance in the HEMS. The DERs and loads have been scheduled using a mixed-integer linear programming [MILP] approach to get the optimum solution. The time horizon has been divided into 24 slots (1 hour each) which could be reduced to compare with a more realistic scenario. A comparative analysis of different strategies to reduce the peak to average ratio (PAR) employed by a HEMS is presented in the study [32]. Different scenarios have been considered based on the rapid change in the tariffs during COVID-19 and modelling is done using MILP and the problem is solved using CPLEX solver of GAMS software.

The comfort level should be considered while scheduling the appliances, especially for thermal appliances. Several studies have neglected this constraint since it makes the problem very complex. There are various ways to lower the cost of electricity; however, peak rebound and PAR should both be considered as constraints simultaneously. Otherwise, the power system will face other challenges as a requirement of extra power reserves and extra expenses on the infrastructure to maintain the reliability of the existing network. Various papers discussed several strategies for power transfer from the grid; still, the applied strategy to limit the import of power from the grid and reduce PAR is not considered in any of the research papers up to the best of the author's knowledge.

In this research paper, gaps found as discussed above have been considered to give more realistic HEMS and contribute to the novelty of this study.

- Nearly all kinds of general-purpose appliances of residential loads are included in DR strategies.
- A renewable energy source is considered in the form of PV which is used to charge BESS and EV. BESS and EV are taken as special loads that can also supply electricity to the home during peak pricing hours.

- Incentive-based DR (IB-DR), with real-time pricing (RTP) based tariff and dynamic peak power limiting strategies, are used to schedule the household appliances to minimize the total electricity cost for the consumer while keeping the rebounding within limits.
- A utility function-based MILP model is formulated and solved to minimize electricity cost and PAR by GAMS-CPLEX.
- A dynamic power import strategy is used for the transaction between grid and household, which the authors do not find in any other research paper to the best of their knowledge.
- All the discussed gaps are included simultaneously in the study, which makes the study novel.

The IB-DR program assists the utility in reducing peak demand for electricity by incentivizing consumers to reduce the promising load. Under the RTP scheme, the reduced load is transferred to the other off-peak time slots to meet the total consumption of the consumer. The demand shifted to off-peak hours, which can cause peak rebounding, will be limited to a predefined value using the applied dynamic peak limiting DR strategy.

The remaining paper is organized as follows: Section 2 consists of a detailed discussion of the HEMS model along with the mathematical model of BESS, EV, solar PV, thermal, and non-thermal characteristics-based appliances. The objective function's mathematical model and the solution to the proposed model are covered in Section 3. The case study and quantitative analysis & findings of various DR programs are addressed in Section 4, which is the results section. Concluding remarks of the study are covered in section 5.

2. Home Energy Management System

2.1. System Model

A single household prosumer is considered to have a small solar PV as a DER, non- thermostatically and thermostatically controllable loads. AC and EWH are taken as thermostatically controllable loads. Some must-run appliances are also included in the study. The ratings of different sources and storage, solar irradiation, and incentives are assumed for this study only. They are not guaranteed to meet the standards. A home energy management unit (HEMU) is employed for scheduling purposes. Scheduling interval is assumed, which is split into 60-minute time slots. Here H is defined as the set of divided hourly time intervals, i.e., $H = \{1,2, \ldots, 24\}$. Different types of loads and appliances are modeled and explained as follows:

2.2. Non - Thermostatically Controllable Appliances:

The energy consumption scheduling vector Q_a is denoted as

$$Q_a \triangleq \left[Q_a^1, Q_a^2, \ \ldots, \ Q_a^{24}\right] \tag{1}$$

where Q_a^h shows the energy consumption of appliance $a \in A$ at time slot *h,* and 'A' denotes the set of appliances employed in the household. Now, let us assume that E_a is the energy required for the complete operation of the appliance' *a'*. Hence, it can be written as

$$\sum_{h \in H} Q_a^h \ = E_a \ \forall a \tag{2}$$

Any appliance $a \in A$ may have a distinct requirement of energy based on its specification and use by the consumer [33]. Various appliances may differ in their operational characteristics.

• *Interruptable loads*: The appliances which can run at any time interval preferred by the consumer are included in this category. These appliances are switchable between ON and OFF at any moment throughout the consumer's chosen time slots. In the ON state, fixed energy is consumed by the appliance, which is shown as Y_a^{max} and in the OFF state, the appliance will consume minimum energy of Y_a^{min}. Thus, the energy consumption of the appliance can be formulated as:

$$Q_a^h = y_{h,a} * Y_a^{max} + (1 - y_{h,a}) * \ Y_a^{min}, \ \ \forall h \tag{3}$$

where $y_{h,a}$ is a binary variable that represents the ON/OFF status of the appliance $a \in A$ (i.e., 1 for ON state and 0 for OFF state). Any appliance must be turned on for a specific amount of time to finish the assigned duty, which can be expressed by

$$\sum_{h \in H} (y_{h,a} * S_{a,h}) = \ k_a \tag{4}$$

The binary variable $S_{a,h}$ is used to choose the operating state of $a \in A$ according to the consumer's selected preferences. k_a denotes the total duration required by the interruptable appliance for the completion of the assigned task ($k_a \leq$ entire ON duration of the appliance a).

• *Uninterruptable loads:* After turning ON, these appliances will turn OFF only if the assigned task is completed. This means we can schedule the ON time only. The uninterruptable loads can be of different load profiles according to their operational characteristics. Another binary variable, x, is introduced for the modeling of such appliances so that

$$\sum_{n \in N} x_{n,a} = 1 \tag{5}$$

where $n = 1, 2, \ldots$ up to *N*. Here, *N* is the total number of possible schedules for appliance '*a'*. Therefore, the energy consumption of the uninterruptable appliances is given by,

$$Q_a^h = \sum_{n \in N} (x_{n,a} * E_{n,h}) \qquad \forall \ h \tag{6}$$

where $E_{n,h}$ is the energy required in the hth slot of the schedule *n*.

Thus, we can say that the total power per time slot, i.e., the energy required by the non-thermostatically controllable appliances, will be:

$$Z_h^{appl} = \sum_{a \in A} Q_a^h \qquad \forall \ h \tag{7}$$

2.3. Thermostatically Controllable Appliances:

Generally, these appliances are the most power-consuming appliances for a household, which also affect the comfort of a residential consumer; therefore, scheduling such devices must be proper to reduce the overall electricity bill. In this study, AC and EWH are included as thermostatically controllable appliances and modeled as follows:

• *Air conditioner (AC) model*: The temperature of the room where the AC is installed affects how well it works. Many factors, like the rate of heat exchange between a house & outside environment, thermodynamic characteristics of the building, and thermal characteristics, affect the inside temperature of the portion [34]. These aspects are taken in mind, and the equations represent a linear form of the model:

$$\begin{aligned} \theta_h^r = & \theta_{h-1}^r + \left(\frac{\Delta t}{M_a * C_a * R_{eq}}\right) * (\theta_{h-1}^a - \theta_{h-1}^r) \\ & - m_{h-1}^{AC} * \left(\frac{\beta * Z^{AC} * \Delta\theta}{0.000277 * M_a * C_a}\right) \qquad \forall \ h > 1 \end{aligned} \tag{8}$$

$$\theta_h^r \leq Spt_h + D_h^u \qquad \forall \ h \tag{9}$$

$$\theta_h^r \geq Spt_h - D_h^l \qquad \forall \ h \tag{10}$$

$$Z_h^{AC} = Z^{AC} * \ m_h^{AC} \forall \ h \tag{11}$$

The temperature inside the room during the cooling operation of AC is represented by (8). D_h^u and D_h^l are the allowable deviation limits in the room temperature from the set-point decided by the consumer according to his comfort level. Equation (11) represents the power consumed by the AC in which, Z^{AC} is the rated power of AC per time slot and m_h^{AC} is a binary variable, the value of which will be 1 when AC is operating.

- *EWH model:* The mathematical model of EWH is taken from [34] with suitable modifications. It is assumed that used hot water from the EWH is replaced with cold water. It is also assumed that the EWH is installed where the ambient air temperature has an immediate effect on the water temperature. The following equations represent the EWH model:

$$\theta_{h+1}^{HW} = \theta_h^a + q\ {*}R{*}m_h^{EWH} - (\theta_h^a - \theta_h^{HW}) * e^{-\frac{\Delta t}{R*C}} \qquad \forall\ h, u_h = 0 \tag{12}$$

$$\theta_{h+1}^{HW} = \frac{\theta_h^{HW} * (V - \ u_h) + \ \theta_h^{CW} {*} u_h}{V} \qquad \forall\ h, u_h > 0 \tag{13}$$

$$\theta_h^{HW} \leq \theta^{HWmx} \qquad \forall\ h \tag{14}$$

$$\theta_h^{HW} \geq \theta^{HWmn} \qquad \forall\ h \tag{15}$$

$$Z_h^{EWH} = q * \ m_h^{EWH} \qquad \forall h \tag{16}$$

where (12) represents the temperature of hot water in the EWH tank due to the heat produced by the resistance of EWH and by the heat exchange from the environment. θ_h^a denotes the outdoor air temperature (°C), q denotes the capacity of EWH (kW), *R & C* denotes the thermal resistance of EWH (°C /kW), and thermal capacitance of EWH (kWh/°C). Equation (13) shows the temperature of water in the tank of EWH after the use of hot water from the tank, where *V* denotes the tank size of EWH (gallons) and u_h is used for hot water usage (gallons/min). The maximum and minimum limits on the temperature of the tank of EWH are determined by (14) and (15), respectively. Finally, the electric energy consumption by the EWH is shown in (16).

2.4. Solar PV Model

In this paper, the customer is considered a prosumer with a small solar PV as a DER. It is assumed that the prosumer has installed the rooftop PV of 1kW in the house. Data from [35] is used to calculate generated PV power. The solar PV-generated power per time slot can be represented by (17).

$$Z_{h\ dc}^{PV\ gen} = \left(\frac{f_{PV}}{0.8}\right) * PV_{rated} * \frac{G_h}{G_{STC}} * \left\{1 + \alpha_T * (\theta_h - \theta_{STC})\right\} \tag{17}$$

The manufacturers provide the datasheet of PV panels for standard test conditions (STC) to indicate their performance. STC has mainly three conditions; irradiance of 1000W/m^2 (G_{STC}), the temperature of cells of the panel at 25°C (θ_{STC}), and the air mass of 1.5. This means PV will provide the rated power PV_{rated} at STC but in the actual scenario, environmental conditions change according to the place where PV is installed. In equation (17), $Z_{h\ dc}^{PV\ gen}$ shows the actual PV generated energy at hth hour, depending on f_{PV} which is a factor to include the effect of dust etc., G_h(W/m^2) is the actual irradiance and θ_h is the actual temperature (in °C) at hth hour. α_T = -0.0048 °C is the temperature coefficient of power. The effective generated solar energy is used for a portion of residential load demand and shown as:

$$Z_h^{PV\ home} = Z_h^{PV\ gen} \qquad \forall\ h \tag{18}$$

2.5. BESS Model

It is assumed in this study that the consumer has installed a BESS unit to store energy. The BESS unit will consume energy in the charging mode and act as an energy source in the discharging mode. Hence the energy provided by the BESS unit for the household will be

$$Z_h^{BESS\ home} = Z_h^{BESS\ dis} * \eta d^{BESS} \qquad \forall\ h \tag{19}$$

where $Z_h^{BESS\ dis}$ is the discharging power and $\eta d^{BESS}$is the discharging efficiency of the BESS. (20) and (21) show the BESS's charging and discharging power (kW).

$$Z_h^{BESS\ ch} \leq Chr^{BESS} * \ m_h^{BESS} \quad \forall\ h \tag{20}$$

$$Z_h^{BESS\ dis} \leq Disr^{BESS} * (1 - \ m_h^{BESS}) \ \ \forall\ h \tag{21}$$

where $Chr^{BESS}/\ Disr^{BESS}$ are the charging / discharging rate of the BESS respectively and m_h^{BESS} is a binary variable value of which will be '1' in the charging mode of BESS during the hour 'h' and '0' otherwise. The state of energy (SE) at a hth hour can be shown as

$$SE_h^{BESS} = SE_{h-1}^{BESS} + \eta ch^{BESS} * Z_h^{BESS\ ch} - (Z_h^{BESS\ dis}/\eta d^{BESS}) \qquad \forall\ h \geq 1 \tag{22}$$

where ηch^{BESS} is the charging efficiency of the BESS and $Z_h^{BESS\ ch}$is the BESS's charging power (kW). The initial SE at the beginning of the time horizon is represented by (23).

$$SE_h^{BESS} = SE^{BESS\ ini} \qquad if\ h = 1 \tag{23}$$

Each battery storage unit has a limit on its maximum and minimum energy state, as shown in (24) and (25).

$$SE_h^{BESS} \leq SE^{BESS\ mx} \qquad \forall\ h \tag{24}$$

$$SE_h^{BESS} \geq SE^{BESS\ mn} \qquad \forall\ h \tag{25}$$

where $SE^{BESS\ mx}$ / $SE^{BESS\ mn}$ are the BESS's maximum and minimum SE range (kWh).

2.6. Electric Vehicle Model

The EV will be included in the DR program between the time of arrival ($H^{ar.}$) and time of departure ($H^{dp.}$) from home. The mathematical model used in the study is presented in the following equations:

$$Z_h^{EV\ home} = Z_h^{EV\ dis} * \eta d^{EV} \qquad \forall\ h \in [H^{ar}, H^{dp}] \tag{26}$$

where $Z_h^{EV\ home}$ is the effective EV power per time slot used for the household demand, and discharging efficiency of the EV is denoted by ηd^{EV}.

$$Z_h^{EV\ ch} {\leq} Chr^{EV} * \ m_h^{EV} \qquad \forall\ h{\in}[H^{ar}, H^{dp}] \tag{27}$$

$$Z_h^{EV\ dis} \leq Disr^{EV} * (1 - \ m_h^{EV}) \qquad \forall\ h \in [H^{ar}, H^{dp}] \tag{28}$$

where, $Z_h^{EV\ ch}$ and $Z_h^{EV\ dis}$ are the EV's charging and discharging power per time slot, respectively, and, $Chr^{EV}$and $Disr^{EV}$ are the EV's charging and discharging rate. m_h^{EV} is a binary variable, the value of which is '1' if it is charging during the interval 'h'; otherwise, its value will be '0'. Equations (27) and (28) depict the EV's charging and discharging power limits. Like a BESS, the SE of an EV at a particular time slot can be represented as in the (29).

$$SE_h^{EV} = SE_{h-1}^{EV} + \eta ch^{EV} * Z_h^{EV\ ch} - (\frac{Z_h^{EV\ dis}}{\eta d^{EV}}) \qquad \forall\ h \in [H^{ar}, H^{dp}] \tag{29}$$

where SE_h^{EV} and SE_{h-1}^{EV} are the SE of the EV at hth slot and (h-1)th slot. At the time of arrival, the EV's SE is shown in equation (30). The maximum and minimum limits on the SE of the EV are shown in (31) and (32).

$$SE_h^{EV} = SE^{EV\ ini} \quad if\ h = H^{ar} \tag{30}$$

$$SE_h^{EV} \le SE^{EV\ mx} \quad \forall\ h \in [H^{ar}, H^{dp}] \tag{31}$$

$$SE_h^{EV} \ge SE^{EV\ mn} \quad \forall\ h \in [H^{ar}, H^{dp}] \tag{32}$$

It is assumed that there is no energy loss in the EV if it is not used in scheduling, and hence SE will remain at the maximum value after full charging until the vehicle's departure, which is modeled in the (33). It is also assumed that the EV is not reused after complete charging; the energy remaining at the EV's arrival is used only. The EV will be at minimum SE if it is fully discharged at a preselected time slot.

$$SE_h^{EV} = SE^{EV\ mx} \quad \forall\ h \ge\ H^{f.ch.} \in [H^{ar}, H^{dp}] \tag{33}$$

$$SE_h^{EV} = SE^{EV\ mn} \quad \forall\ h =\ H^{f.dis.} \in [H^{ar}, H^{dp}] \tag{34}$$

All the variables considered in the modeling of the EV will be functional only if the EV has arrived at the home; otherwise, the value of all the variables will be zero, which is shown in (35).

$$\begin{aligned} Z_h^{EV\ home} &= Z_h^{EV\ so} = Z_h^{EV\ dis} \\ &= Z_h^{EV\ ch} = 0, \quad \forall\ h \in H/[H^{ar}, H^{dp}] \end{aligned} \tag{35}$$

2.7. Incentive-Based Demand Response (IB-DR) Modelling

A residential community is considered in this study, and the participation of a consumer is presented as:

$$cost(h) = Z_h^{DR} * \partial^{DR} \tag{36}$$

$$Z_h^{DR} \le z_h^{mx} \tag{37}$$

where $cost(h)$ is the total cost of consumer's participation in the DR program, Z_h^{DR} is the planned saving in the must-run load and $\partial^{DR}$is the consumer incentive given at hour h, respectively. The customer's participation in the IB-DR program is optional, but the study is done for the customers who willingly participate. The incentive can be fixed or dynamic, depending on the price sensitivity and load elasticity. For this case study, a flat rate of 3.5 cents is used as the incentive (∂^{DR}). However, according to the available load for participation in the DR, incentives may also have different values, as mentioned in Table-2.

2.8. Power Import Limits

The maximum power limit per slot which can be imported from the grid is shown by (38).

$$Z_h^{gr} \le A_{mx}(h) \forall\ h \tag{38}$$

Here $A_{mx}\ (h)$ is a set of positive integers representing the power import limit at each hour. In this study, dynamic power import limit (DPIL) is used, which is different for each hour. The limit is set according to the real-time price, demand of the consumer, and the constraints which must be satisfied to get the feasible solution of the objective function. For this, a higher power import limit is used in this study during the hours at which the RTP is low and/or the demand of the consumer is high. The limits considered are shown in Fig. 1. However, a separate algorithm can also be implemented to calculate the power limit at each slot. It would be beneficial to build and use such algorithms if the scope of the study has to be increased to a large number of consumers, which is not a part of the current study.

3. Problem Formulation And Proposed Solution

3.1. Problem Formulation

The study's primary goal is to reduce the cost of household electricity consumption by utilizing local sources in conjunction with the DR strategy. The proposed problem's objective function is written as follows:

$$Cost = \sum_{h \in H} \left(Z_h^{gr} * \partial_h^{buy} -\ Z_h^{DR} * \partial^{DR} \right) \tag{39}$$

Equation (39) shows the difference between the grid's electricity price and the cost for the customer's participation in the DR at hour 'h'.

Now, the DPIL strategy is modified in such a way that if the customer wants to use extra power per time slot (Z_h^{ex}) besides pre-specified limits, he can use it but at a higher price. That's why modified objective function and DPIL will be changed as:

$$Z_h^{gr} \le (A_{mx} + Z_h^{ex}) \quad \forall\ h \tag{40}$$

$$Cost = \sum_{h \in H} \left((Z_h^{gr} -\ Z_h^{ex}) * \partial_h^{buy} + Z_h^{ex} * \left(x * \partial_h^{buy} \right) -\ Z_h^{DR} * \partial^{DR} \right) \tag{41}$$

Where 'x'is a factor, the value of which is greater than one and depends on the tariff for the extra power. In this study, the value of 'x' is assumed to '1.1', yet it is not a standard value referenced in any article. According to the DR program strategy, the power utilized by the home for must-run appliances, thermal and non-thermal appliances, EV, and BESS charging will be supplied by the grid, PV, EV, and BESS. The energy balance equation can be written as:

$$Z_h^{gr} + Z_h^{PV\ home} + Z_h^{BESS\ home} + Z_h^{EV\ home} = (Z_h^{MR} -\ Z_h^{DR}) +\ Z_h^{appl} + Z_h^{BESS\ ch} + Z_h^{EV\ ch} + Z_h^{AC} + Z_h^{EWH} + Z_h^{ex} \forall\ h \tag{42}$$

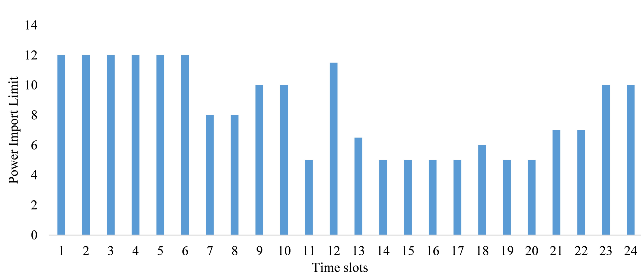

Fig. 1. Hourly power limits used in the study

Here in (42), parameters are the effective power, including conversion efficiency. However, the conversion efficiency has not been focused.

The formulated problem is comprised of various constraints, shown by (1)–(42) except (39) and (41). The constraints are of binary or integer values. The objective functions of the study are shown in (39) and (41). The objective function is linear; hence, it does not create complexity and is solvable using mixed integer programming (MIP) techniques. The CPLEX solver of GAMS software can be used for solving MIP and MILP problems [36]. Hence the problem is solved using the CPLEX solver of GAMS on a 64-bit, intel core i5-1035G1 CPU @1.00GHz laptop.

Table 1. Specifications for non-thermostatically controlled appliances

Appliance	Type	Avg. power (kW)	Time of operation (hours)	Energy consumed per day (kWh)
Water Pump	1	0.75	3	2.25
Vacuum cleaner	1	0.74	2	1.48
Dryer	2	5.5	1	5.5
Coffee maker	2	0.35	1	0.35
Range Top (S)	2	1.6	1	1.6
Microwave oven	2	0.8	1	0.8
Iron box	2	1.1	1	1.1
Toaster	2	1.1	0.5	0.55
Toaster Oven	2	1.5	0.5	0.75
Oven cleaner	2	3.5	0.5	1.75
Washing machine	2	0.665	1.5	0.9975
Dish washer	2	1.2	1.5	1.8
Oven	2	3.5	1.5	5.25

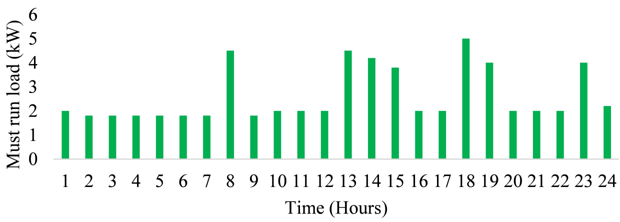

Fig. 2. The average power demand of household must run appliances

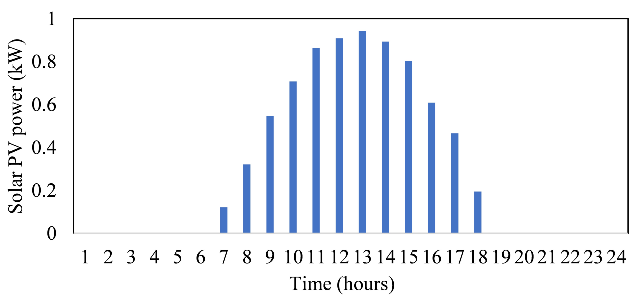

Fig. 3. Solar power generated by PV panels

4. Case Study And Result Analysis

The commonly used appliances used by any household customer are taken in this study. The data on the daily demand for must-run appliances (refrigerator, TV, telephone, etc.) [37] is done by averaging the monthly consumption of the appliances, shown in Fig. 2.

The data for non-thermally controlled appliances are shown in Table 1, which is taken from [33], and the PV power generated from the solar panels is shown in Fig. 3.

For the customer's comfort, his preferences are required for the use of thermal appliances. In this study, AC and EWH are considered as thermally controlled appliances. It is assumed that he needs the room temperature between 23°C to 27°C from 10 AM (11^{th}-time slot) to 5 PM (18^{th}-time slot). Other parameters for the function of AC are as follows. The mass of air is 1778.369 Kg, the thermal capacity of air is 1.01 KJ/Kg ^{0}C, the equivalent thermal resistance is 3.1965*10^{-3} h.°C/KJ, coefficient of performance is 2, thermostat set point is at 25°C, allowed deviation in temperature around the set-point is set to 2 °C, and the power rating of the AC is taken 2 kW.

4.1. Proposed Solution

The thermal properties of the EWH are derived from [23], with a rated power of 2kW and a water capacity of 50 gallons assumed. For the scheduling of the EWH, it is assumed that the customer will be needed hot water at 6 AM and 6 PM, which are the 7^{th} & 19^{th} slots of the time horizon. The temperature range of hot water is assumed to be 30°C to 45°C and 30°C to 50°C, respectively, for selected slots. The showerhead is assumed to have a flow of 2.5 gallons/min and supplies water for 10 minutes after getting ON.

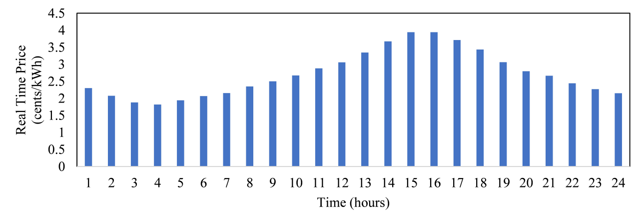

Fig. 4. Real-time price tariff

It is also assumed that the customer has the BESS capacity of 1 kWh with an initial SE of 0.5 kWh. The charging/discharging rate is taken as 0.2 kWh, and the efficiency is assumed to be 0.95. The permissible limit on the discharge of the BESS is up to 0.25 kWh.

In this study, EV can work in the home to vehicle (H2V) and V2H mode for better utilization of EV. In V2H mode, the remnant energy of EV can be utilized for the demand for home appliances. The battery capacity of the EV is assumed to be 16 kWh, with a charging/discharging rate of 3.3 kWh [38] and an efficiency of 0.95. The minimum SE level of the EV's battery is believed to be 4.8 kWh in order to prevent deep discharge of the battery [39].

In this study, an RTP tariff is used for purchasing power from the grid. The data for RTP tariff is taken from [40] and shown in Fig. 4 in which the price is varied in each hour of the day. In this study, energy from PV and other local sources is used in the home itself; therefore, the transfer of energy to the grid is not taken into account. The utility offers several options for consumer participation in an IB-DR program. Based on experience, the utility informs customers about the DR program's implementation time and incentive rates prior to scheduling. The reward rates can be different for different DR values. In this study, the reward rates are taken as shown in Table 2, although these are not standard rates but only from the analysis point of view.

In this study, the customer is bound with 40% of the must-run load dedicated to the DR program during peak hours. The time horizon is divided into 24 hourly slots. The time between 1 PM to 7 PM is taken as peak hours. The consumer has opted for the option in which 33% of the committed load is selected for the DR program.

Different scenarios have been considered in the study for the scheduling of appliances and the local sources according to the preferences of the customer. The impact of scheduling on the electricity cost and PAR is considered for each scenario. All the scenarios (except I) are modelled as MILP and analyzed using CPLEX solver GAMS software. Different scenarios are described as:

Table 2. Rates of incentive for various DR levels

DR level	33% of the committed load for DR	66% of the committed load for DR	100% of the committed load for DR
Incentive rate (cents/kWh)	3.5	4	4.5

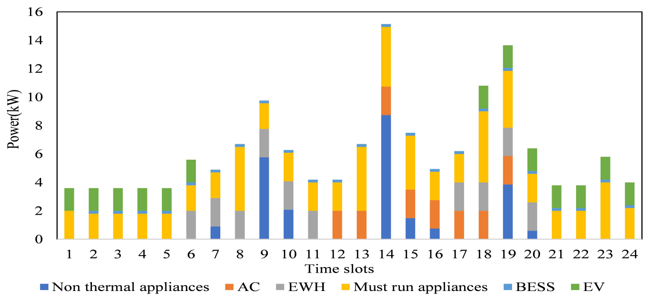

Fig. 5. Typical scheduling of household appliances without any DR program.

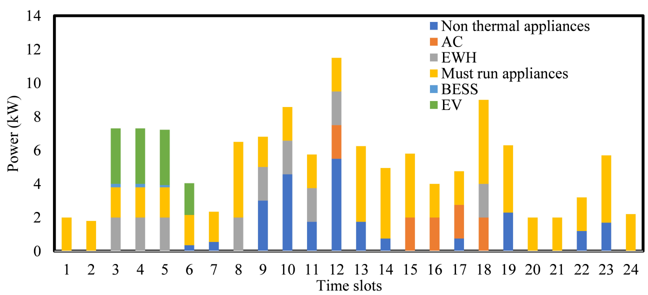

Fig. 6. Scheduling with RTP-based DR having DPIL and without IB-DR

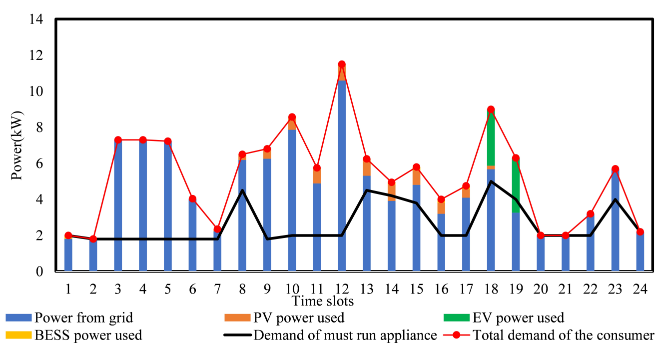

Fig. 7. Contribution of different power sources towards the household demand for scenario- II.

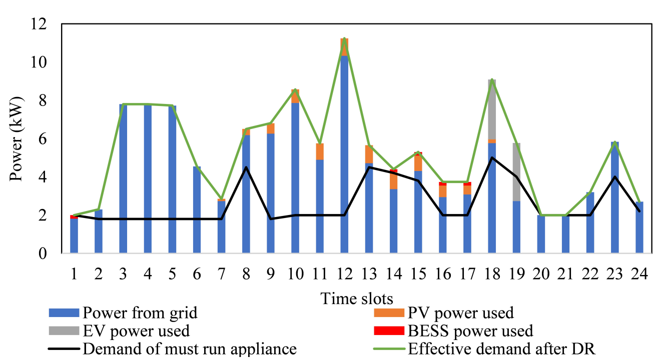

Fig. 8. Contribution of different power sources towards the household demand for scenario- III.

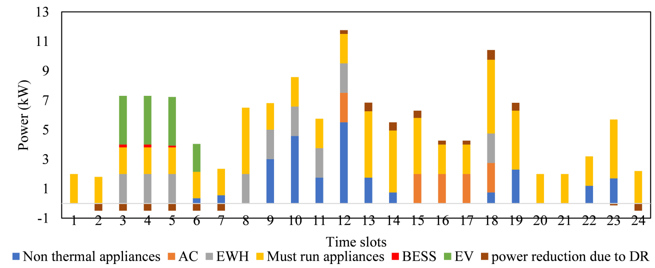

Fig. 9. Scheduling with RTP-based DR having DPIL and with IB-DR.

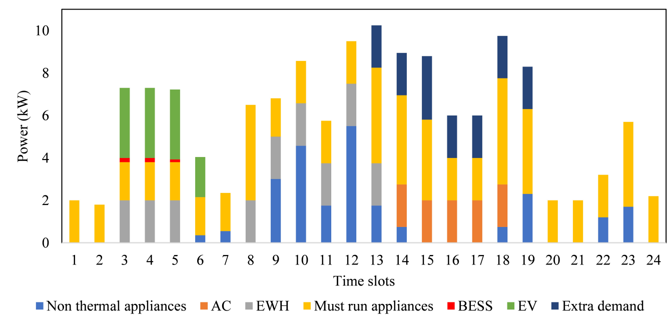

Fig. 10. Scheduling with RTP-based DR having peak pricing-based dynamic power import limiting DR during extra demand hours and without IB-DR.

I. Typical scheduling of household appliances without RTP-based and IB-DR.
II. Scheduling with RTP-based DR having DPIL and without IB-DR.
III. Scheduling with RTP-based DR having DPIL and with IB-DR.
IV. Scheduling with RTP-based DR having peak pricing-based dynamic power import limiting DR during extra demand hours and without incentive-based DR.
V. Scheduling with RTP-based DR having peak pricing-based dynamic power import limiting DR during extra demand hours and with incentive-based DR.

In scenario-I., the consumer has no DR program, and typical scheduling according to the consumer's preference is shown in Fig. 5. In this study, EV can work in the home to vehicle (H2V) and V2H mode for the better utilization of EV.

It is clearly be seen in Fig. 5 that peak demand is 15.1 kW at the 14^{th} time slot and several other peaks during the high-cost slots. The average demand is found to be 6.18 kW, and therefore, PAR is calculated to be 2.448889. According to the RTP tariff, the total cost of this typical scheduling is calculated to be 404.3678296 cents. Higher PAR also causes more stress in the system and increases the losses, which is why it should be as low as possible (≥ 1). Hence DPIL is used in other scenarios to limit the powers in each slot.

In scenario-II., an RTP-based DR strategy is implemented to schedule the home appliances, EV, BESS, and must-run appliances, as shown in Fig. 6. Different limits are used to limit the power imported from the grid. The limits are varied from 5 kW to 12 kW. Some slots needed high powers in the high price slots due to the customer's preference; that's why limits are higher in those slots to make the scheduling feasible. It can be seen from the results that EV, EWH, and non-thermal loads are shifted towards low price slots, which has an impact on the overall price of electricity. The

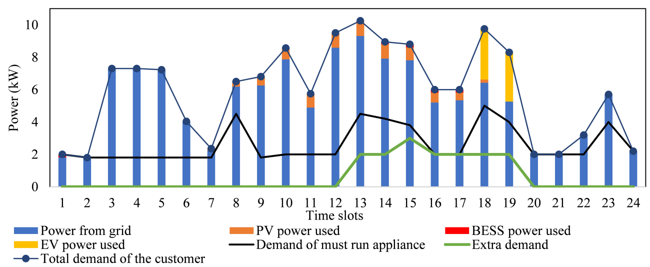

Fig. 11. Contribution of different power sources towards the household demand for scenario- IV.

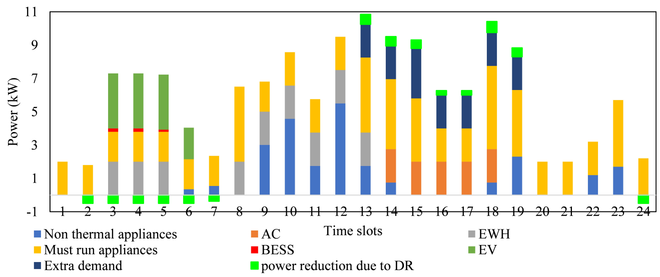

Fig. 12. Scheduling with RTP-based DR having peak pricing-based dynamic power import limiting DR during extra demand hours and with IB-DR.

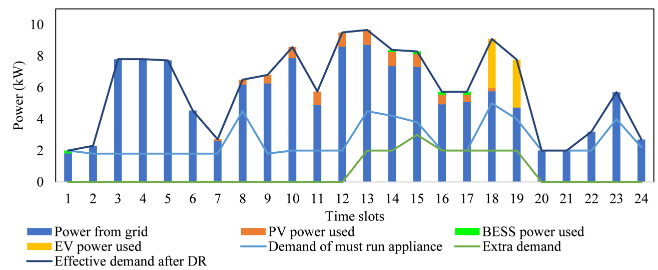

Fig. 13. Contribution of different power sources towards the household demand for scenario-V.

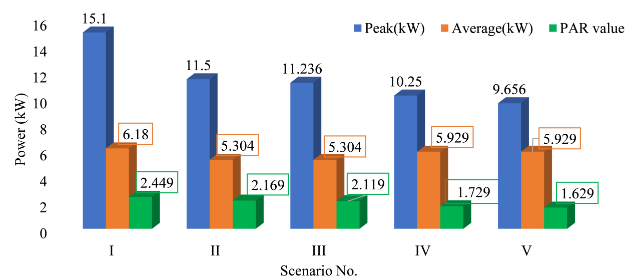

Fig. 14. Variation of peak demand in different scenarios.

energy consumption cost in this scenario is 305.23 cents.

The results shown in Fig. 6 show that scheduling causes the reduced peak concerning scenario- I. While the 1^{st} case's load curve has a peak of 15.1 kW, the peak demand is 11.5 kW, and the average load is 5.303887061 kW. Thus, we can calculate the PAR of the load curve equal to 2.16822113, which is lower than the previous case. The RTP-based DR program with the DPIL strategy has reduced the overall cost and reduced PAR. The contribution of PV generation, BESS, and EV storage power utilization, and the grid imported power is shown in Fig. 7.

In scenario-III., an IB-DR is also implemented with the RTP-based DR program. The IB-DR is implemented for the 12^{th} slot up to the 19^{th} slot. The customer has to reduce 33% of its committed load in these slots, and he will be rewarded with the incentive of 3.5 cents/kWh. The reduced load can be shifted towards other slots. The contribution of different power sources toward the overall power consumption of the residents is represented in Fig. 8.

It can be noticed in Fig. 9 that there is a power reduction in the slots from 12^{th} up to $19^{th,}$ and the reduced load is shifted towards other slots having low prices. Due to the IB-DR program, the total cost of energy consumption is reduced to 286.95 cents. The IB-DR program also reduces the peak power demand, which is also shown in Fig. 9. The 12th to 19th slots' positive toppings show the planned reduction, and the negative increment in other slots shows the load shift in these slots. As a result, the peak demand has been reduced to 11.236 kW, the average demand has remained constant, and the PAR has been changed to 2.118446315.

In scenario-IV., it is assumed that the customer demands extra power in some of the peak hours (13^{th} to 19^{th} slots). For this extra power, the customer has to pay 10 % higher than the predecided tariff. The DPIL limits are modified according to the extra demand in these slots, and scheduling is done with RTP based DR program without IB-DR. The resulted scheduling is shown in Fig. 10. The peak pricing-based dynamic power import limiting strategy causes an increase in the electricity cost due to extra power demand. In this scenario, the electricity cost is 365.66 cents. The PAR of the load curve is calculated as 1.728823621. The contribution of different power sources toward the household's total power demand is represented in Fig. 11. It can be seen that, EV is not utilized as a source after complete charging.

In scenario-V., the IB-DR is also applied with RTP-based DR having peak pricing-based dynamic power import limiting DR during extra demand hours. All the implementation is the same as in scenario-III except that the IB-DR is implemented for the 13^{th} slot up to the 19^{th} slot. Modified DPILs are used as constraints to limit the power in peak hours. The scheduling of the appliances is shown in Fig. 12. The positive increment in the load curve shows the reduction in the demand for must-run appliances, and the negative increment shows an increase in the demand for must-run appliances. These increments show the shift of demand related to must-run appliances. After implementing the DR program, the electricity consumption cost is 348.73 cents in this scenario, which is reduced compared to the last scenario due to the incentive paid to the customer for participating in the DR program. The load curve's peak demand is found to be 9.656, and the average of the effective demand is 5.928887061. Thus, PAR can be calculated as 1.628636184. The contribution of different power sources toward the household demand for scenario-V. is shown in Fig. 13.

Finally, Table 3 summarises the findings to present a comprehensive analysis of all scenarios. It can be observed from Table 3 that without any scheduling strategy, the customer has to pay 404.36 cents for the electricity for the same RTP tariff with PAR equal to 2.45 (2.448889 is written as 2.45). PAR is not a significant concern for the customer but for the utility; it plays a primary role. Higher peaks will cause stress in the network and also increase the requirement of reserves to supply these peak demands. The reserves are more costly than the base power generation, so the tariff also changes accordingly. Any DR program can be practically successful if it benefits the customer and the utility.

For the reduction of PAR and cost, dynamic limits are imposed on the power imported from the grid, resulting in a cost reduction from 404.36 to 305.23 cents, which is a significant margin. PAR is also improved from 2.45 to 2.17. The implemented IB-DR program was opted by the customer for reducing 33% of its accepted load (40% of must-run appliance demand). The customer received the incentive in accordance with Table 2, and when the IB-DR is implemented, the cost is even further lowered by 29.04 % to 286.95 cents, and the PAR is decreased by 13.52 % to 2.11. If the consumer can further lower his load, he will receive a more significant incentive from the utility.

In scenarios-IV. & V., the customer demanded extra power during peak hours, for which the customer had to pay 10% more than the normal tariff. This extra power affected the cost, increasing to 365.66 cents in scenario-IV. However, these

Table 3. Comparative analysis of different case studies

Scenario No.	Description	The energy consumption cost (in cents)	Incentive given (in cents)	PAR value
I	Typical scheduling of household appliances without RTP based and incentive-based DR.	404.3678296	-	2.448889
II	Scheduling with RTP-based DR having DPIL and without IB-DR.	305.2264	-	2.16822113
III	Scheduling with RTP-based DR having DPIL and with IB-DR.	286.9472	12.705	2.118446315.
IV	Scheduling with RTP-based DR having peak pricing-based dynamic power import limiting DR during extra demand hours and without incentive-based DR.	365.6581	-	1.728823621
V	Scheduling with RTP-based DR having peak pricing-based dynamic power import limiting DR during extra demand hours and with incentive-based DR.	348.7336	11.781	1.628636184

additional demands also enhanced the average demand, which caused a further reduction in PAR up to 1.73. Scenario-V shows the participation of the customer in the IB-DR program, due to which the electricity cost is reduced from 365.66 to 348.73 cents. PAR, in this scenario, is found to be 1.63. Fig. 14 makes it simple to see how peak demand and PAR vary. Peak demand is calculated to be reduced by 36.05 %, while PAR is reduced by 33.48 %, when comparing scenario-V to scenario-I. Charging of EV and BESS can also be seen in the graphs shown as scheduling, and discharging can be observed in the figures named as the contribution of power sources.

5. CONCLUSION

This paper includes a HEMS for scheduling extensively used household appliances. Mathematical modelling of thermal appliances, PV, BESS, and EV with their operational constraints are explained in detail. Scheduling considers the consumer's comfort level, and all the appliances are scheduled in the consumer's preferred slots only. The objective function is formulated as a MILP problem to reduce the cost of electricity consumption, which is successfully solved using GAMS' CPLEX solver. Electricity cost is the main focus for any customer, but from the utility point of view, PAR must be improved, which is beneficial for the utility. For the cost reduction and improvement of the PAR, appliances are scheduled using the DPIL strategy. Peak rebounding is also limited by applying the DPIL strategy, which also contributes to the grid's reliability and stability. Different scenarios are discussed with the implementation of IB-DR with DPIL strategy, which caused further decrement in electricity cost. The used thermostatically controlled devices are scheduled according to the customer's preference to maintain the comfort of the customer. Based on the results, it is noteworthy that total energy costs are reduced by 29.03 % with a PAR reduction of 13.49%, comparing scenario-III with the considered base case (scenario-I), which shows the effectiveness of the applied strategies simultaneously for HEMS.

This study considers that the EV will not be utilized for home appliances after complete charging. However, if the price in V2H mode is less than the utility tariff and the vehicle has enough time to get charged again, it can be utilized for household usage. This can also be an extension of this study.

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