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Energy Efficient Integration of Renewable Energy Sources in the Smart Grid for Demand Side Management

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ABSTRACT With the emergence of smart grid (SG), the consumers have the opportunity to integrate renewable energy sources (RESs) and take part in demand side management. In this paper, we introduce generic home energy management control system (HEMCS) to efficiently schedule the household load and integrate RESs. The HEMCS is based on the genetic algorithm, binary particle swarm optimization, wind-driven optimization (WDO), and our proposed genetic WDO algorithm to schedule appliances of single and multiple homes. For energy cost calculation, real-time pricing (RTP) and inclined block rate schemes are combined, because in case of only RTP, there is a possibility of building peaks during off-peak hours that may damage the entire power system. Moreover, to control the demand under the grid station capacity, the feasible region is defined and a problem is formulated using multiple knapsack. Energy efficient integration of RESs in SG is a challenging task due to time varying and their intermittent nature. The simulation results show that the proposed scheme avoids voltage rise problem in areas with high penetration of renewable energy. Moreover, the proposed scheme also reduces the electricity cost up to 48% and peak to average ratio of aggregated load up to 37.69%.

INDEX TERMS Renewable energy sources, demand side management, load scheduling, meta-heuristic techniques, trading/cooperation.

I. INTRODUCTION

Traditional electric grids are inefficient to meet the modern challenges, i.e., renewable energy (RE) integration, distributed generation (DG) and demand side management (DSM). In this regard, smart grid (SG) has emerged as a smart solution which integrates traditional power systems with information and communication technologies (ICTs) and enables two-way communication between utility and consumers [1]. It also incorporates RE sources (RESs), energy storage systems (ESSs), smart meters, distributed storage (DS) and sensors. Moreover, it encourages user participation for energy savings, cooperation through demand response (DR) mechanism and trading among prosumers [2].

RESs are greener alternative to fossil fuel and key contributors for the SG. Therefore, an energy efficient integration of RESs has increased in recent years. It was recorded in 2014 that wind, solar and biomass power plants provided 60% electricity in Denmark, about 30% of electricity demand in Portugal was supplied by non-hydropower renewable and Spain had 29% of RE generation [3]. However, the energy efficient integration of RESs in SG poses significant challenges from both RE and power grid sides. From the RE side, to handle intermittent nature of RESs due to varying weather conditions is a challenging task. From the power grid side, harmonics, voltage and frequency fluctuations due to power electronic devices is a challenge. Energy storage and load scheduling by DR are effective to mitigate stochastic and intermittent nature of RE generations [4], [5].

DSM has been developed since early 1980s to balance the time varying demand of consumers and generation capacity of power systems. Zhao *et al.* [6], perform the optimal scheduling of appliances by employing genetic algorithm (GA). This model reduces the electricity cost and peak to average ratio (PAR) while using real time pricing (RTP) plus inclined block rate (IBR) tariffs. However, the objectives are achieved at the cost of user comfort. Another relevant work in [7], utilizes heuristic based energy management controller (EMC) to optimally schedule appliances in the presence of time of use (ToU) plus IBR tariff and achieves the objectives: electricity bill reduction, PAR minimization and user comfort maximization. However, reducing electricity bill and PAR results in less user comfort because of the tradeoff between cost and user comfort. The EMC based on the harmony search differential evolution (HSDE) algorithm, for home energy management (HEM), is proposed in [8]. The EMC schedules appliances while taking energy from both utility and RESs and considers RTP tariff for billing systems. However, the electricity bill saving is increased at the expense of user comfort. The intelligent residential energy management system (IREMS) is used for the optimal scheduling of household appliances and sizing of RESs and ESS [9]. The electricity cost is reduced and the revenue is increased using GA. However, users's categorization and trading surplus energy is not considered between the users.

Hence, in this paper, we focus on energy efficient integration of RESs with the battery storage in smart homes, where, load is scheduled using heuristic techniques. In this regard, we propose an architecture to efficiently schedule household loads and integrate RESs for minimizing the difference of demand and supply. The distinctive features of our proposed work are given as follows:

1) We design a HEM control system (HEMCS) having an energy management control unit (EMCU) to schedule household appliances under the DSM framework. Furthermore, the appliances are categorized as: smart appliances (SAs) and traditional appliances (TA). To schedule the appliances optimally, SAs are further classified into three categories: power elastic appliances, time elastic appliances and essential appliances. The EMCU schedules appliances for a single home and multiple homes using four different meta-heuristic techniques: the evolutionary algorithm called GA, equation based optimization algorithm known as binary particle swarm optimization (BPSO), population based scheme which is wind driven optimization (WDO) and our proposed genetic WDO (GWDO) algorithm. The simulations are performed to analyze the significance of each earlier said optimization scheme against the parameters of user comfort, PAR and electricity cost.
2) The challenge of RESs (stochastic and intermittent nature for energy generation) is handled by integration of ESS and energy trading among consumers. In this regard, residential consumers are divided into three categories: grid energy consumer (GEC), smart energy consumer (SEC) and trading energy consumer (TEC). In addition, consumers with excess power generation compete to trade excess generation with neighboring consumers to increase the revenue and reduce the reverse power flow.

The rest of the paper is organized as follows. Related work is presented in Section II. In Section III, the system model is introduced. Problem formulation is discussed in Section IV. Section V describes the results obtained through extensive simulations and the findings of the proposed work are presented in Section VI.

NOMENCLATURE

A_n^t	Set of all appliances
SA	Set of smart appliances
TA	Set of traditional appliances
A_{pe}^s	Set of power elastic appliances
p_r^i	Power rating of an appliance
E_T^{pe}	Energy consumption of power elastic appliances
X_t	Indicate status of an appliance
C_T^{pe}	Daily electricity cost of power elastic appliances
$\varphi(t)$	Electricity cost per timeslot
T_h	Scheduling time horizon
A_{te}^s	Set of time elastic appliances
E_T^{te}	Energy consumption of time elastic appliances
C_T^{te}	Total electricity cost of time elastic appliances
A_{ea}^s	Set of essential appliances
E_T^{ea}	Total energy consumption of essential appliances
C_T^{ea}	Total electricity cost of essential appliances
$E_c^i(t)$	Energy consumption of each appliance i at timeslot t
E_T^i	Aggregated energy consumption of all set of appliances
$RPI(E)$	Combined RTP and IBR function
E_{th}	Threshold energy consumption
$D_g(t)$	GEC energy demand per timeslot
D_{gmax}	GEC maximum energy demand
$E_g(t)$	GEC energy consumption per timeslot
E_g	GEC aggregated energy consumption
$D_s(t)$	SEC energy demand per timeslot
D_{smax}	SEC maximum energy demand
$R_s(t)$	SEC harvested RE
$D_s^u(t)$	SEC unsatisfied demand
$B_{d,s}^e(t)$	Energy drawn by SEC from their ESS
$R_{s,T}(t)$	SEC borrowed energy from TEC
$S_{b,s}^e(t)$	Initially stored energy in ESS of SEC at per timeslot
$S_{b,s}^{e,\min}$	Lower limit of ESS of SEC
$S_{b,s}^{e,\max}$	Upper limit of ESS of SEC
$D_T(t)$	Energy demand of TEC
D_{tmax}	Maximum demand of TEC
$R_T(t)$	Harvested RE of TEC
$D_T^u(t)$	Unsatisfied demand of TEC
$B_{d,T}^e(t)$	Energy drawn of TEC from ESS

$R_{T,n}(t)$	Energy exchange among TEC
$S^e_{b,s}(t+1)$	Energy stored in next timeslot in the ESS of SEC
$B^{e,\max}_{d,s}$	Maximum energy drawn from ESS of SEC
$S^{e,\min}_{b,T}$	Lower limit of ESS of TEC
$S^{e,\max}_{b,T}$	Upper limit of ESS of TEC
$B^{e,\max}_{d,T}$	Maximum energy drawn from ESS of TEC
S^{sa}_t	State of SA at each timeslot
r^n_t	Number of remaining timeslots
w^n_t	Number of waiting timeslots
S^{pe}_t	Initial state of power elastic appliances
S^{pe}_{t+1}	State of power elastic appliance at next timeslot
S^{te}_t	Initial state of time elastic appliances
S^{te}_{t+1}	State of time elastic appliance at next timeslot
S^{ea}_t	Initial state of time elastic appliances
S^{ea}_{t+1}	State of time elastic appliance at next timeslot
C^e_T	Total electricity cost
A^p_r	Peak to average ratio
T^o_s	Operation timeslots of an appliance
C_w	Waiting time cost
μ_i	Time factor of an appliance
A_i	Arrival timeslot of an appliance
$Capacity$	Capacity of the grid
α	Start time of interval
$C^e_{s,T}(t)$	Cost of per unit energy transfer of SEC from TEC
$C^e_{T,n}(t)$	Cost per unit of energy exchange among neighboring TEC
$C^e_g(t)$	Cost of the energy transfer from electricity grid station
$\mathrm{Cost}_{\mathrm{GEC}}$	GEC cost
$\mathrm{Cost}_{\mathrm{SEC}}$	SEC cost
$\mathrm{Cost}_{\mathrm{TEC}}$	TEC cost
β	End time of interval
$C^{e,\max}_g$	Maximum cost of the energy transfer from electricity grid station
$C^{r,\max}_{s,T}$	Maximum cost of per unit energy transfer of SEC from TEC
$S^e_s(t)$	Energy stored at each timeslot in ESS of SEC
$S^e_T(t)$	Energy stored at each timeslot in ESS of TEC
$R_T(t)$	Renewable energy harvested by TEC

II. RELATED WORK

In order to optimally schedule a household load and integrate RESs, numerous techniques have been presented in the literature. Two different techniques are described to mitigate intermittent nature of RESs in [10]. The first one is the storage system, which smooth out fluctuations of RE obtained from RESs. The second technique is the concept of DG combined with cooperation by exchanging energy among distributed sources. This technique averages out variations in energy production across space. The objective is to minimize average cost of energy exchange within the grid. However, reduction in the number of peak power plants and frequency of interruption are not addressed. An alternate method, to mitigate stochastic and intermittent nature of RESs is fast-ramping fuel-based generator as a backup. However, this method is not cost effective and environmentally friendly.

Liang and Xiaodong [11] presented power quality challenges due to integration of RESs. The engineering complexity in the integration of RESs to grid is twofold: (i) voltage and frequency fluctuations, which are caused by non-controllable variability or intermittent nature of RESs and ii) harmonics which are caused by the power electronic devices. However, cooperation among RE generating users are not considered by the authors.

Li *et al.* [12] proposed a real time residential side joint energy storage management and load scheduling model with RESs integration, under the assumption that RESs, load and electricity price (EP) are unknown. The authors use the lyapunov optimization technique to tackle finite time horizon stochastic problem. In addition, they also use a real time algorithm for joint load scheduling and energy storage control to minimize the overall system cost. The simulation results demonstrate that the proposed scheme is efficient in reducing the system cost. However, the authors have ignored cooperation among RE generating consumers and residential load classification.

Zhao *et al.* [6] have investigated optimal power scheduling method for DR in HEM system (HEMS). The scheduling of appliances helped in the reduction of electricity consumption cost and avoidance of PAR. Moreover, the energy management system (EMS) is integrated with a home area network (HAN) based on RTP with IBR models. The effectiveness of the schemes is validated via conducting extensive simulations and it is concluded that the proposed scheme outperforms the compared schemes in terms of electricity bill and PAR at the cost of user comfort.

An efficient heuristic approach in [7] presented to utilize EMC with RESs. For the EP computation, combined model of ToU with IBR tariffs is used. The problem formulation is carried out via multiple knapsack (MK). The heuristic based EMC performs more efficiently in terms of the electricity bill reduction, PAR minimization and user comfort maximization. Simulation results show that the designed model significantly achieves required objectives and hence increases sustainability of SG. However, when reducing the electricity cost, the user comfort increases because of inverse relation between cost and comfort.

Kazmi *et al.* [8] proposed an algorithm for providing incentive based scheduling for the optimal energy consumption. DR with ToU pricing program is used to reduce the energy demand during peak hours. BPSO based HEMS schedules the appliances and RESs for reducing the electricity bill. However, the issues of user comfort and challenges of RESs integration are neglected.

Arun and Silvan [9] proposed IREMS for dynamic DR in smart buildings. The IREMS schedules appliances during low-price slots while considering operational dynamics of non-schedulable load and intermittent nature of RESs and maintaining the power demand subjected to various constraints in order to reduce the electricity cost. The RESs and battery storage systems are optimally sized using the GA. Furthermore, the IREMS ensures effective utilization of RESs by optimally controlling the battery operation and properly scheduling the schedulable load.

An intelligent multi-agent control system (MACS) is proposed in [13] to optimize the electricity use and enhance the user comfort in smart buildings. Intelligent MACS with heuristic optimization is designed for reducing the energy consumption without compromising the user comfort and pressure on environment. A graphical user interface (GUI) based platform is also developed to provide flexibility to users to input their preferences and monitor the results. Agents are divided into four types to coordinate and perform their tasks efficiently. The simulation results show that intelligent MACS efficiently achieves the desired objectives. However, the issues of minimizing appliances' waiting time, PAR and demand curve smoothing are not discussed.

Agent based control for decentralized DSM (DDSM) is used to manage the demand on a large scale in SG [14]. Evolutionary game theoretic techniques (EGTTs) are used to motivate consumers to adopt an agent based smart meter. In this mechanism, the agents coordinate in a decentralized manner to optimize the consumption patterns. The results show that the proposed scheme is efficient in terms of: (i) peak demand reduction, (ii) carbon emission and (iii) decentralized DG. However, authors have ignored power quality issues accompanied with DG.

Hafeez *et al.* [15] proposed a heuristic based EMCU to schedule the household in order to reduce cost and PAR. In addition, they handle the RESs integration by ESS and cooperation among the consumers in order to reduce the reverse power flow. Javaid *et al.* [16] presented an efficient model of the DSM that reduces the PAR and electricity bill for residential, industrial and commercial users. The scheduling problem is formulated as a minimization problem and evaluated using a heuristic evolutionary approach. The proposed model is beneficial for both utility and customers. However, the issues such as user comfort, reduction in power consumption and pressure on the environment are not discussed.

A residential power scheduling for DR in SG is proposed for optimal scheduling of smart appliances in order to minimize the tradeoff between the electricity payments and discomfort [17]. The power scheduling is formulated as an optimization problem including integer and continuous variables under three operation modes. In addition, an optimal scheduling of appliances is achieved by using integer liner programming (ILP). The simulation results show that scheduling strategy is effective in achieving desired objectives. However, the proposed scheme achieves objectives at the cost of increased system complexity and execution time.

The load scheduling and power trading in systems with high penetration of RESs is presented in [18]. Authors adopt approximate dynamic programming to schedule operation of must-run and controllable appliances and game theoretic approach to model trading among users with excess power generation. They formulate a problem of joint load scheduling and power trading in order to increase the revenue and reduce the electricity cost. The simulation results show that the scheme is effective in achieving the desired objectives. However, the challenges accompanied with integration of RESs are not mentioned.

Phuangpornpitak and Tia [19] investigated the opportunities and challenges of RESs integration in SG systems. With the integration of RESs, the objectives achieved are as follow: (i) increase the reliability of the grid and (ii) reduce the number of peak power plants. However, the stochastic nature of the RE is an obstacle to the RESs integration into the SG.

Rahbar *et al.* [20] proposed an energy cooperation optimization in microgrids with RESs integration. The energy management problem is handled by two models of microgrid cooperation. First, an energy management is preformed through the off-line optimization by assuming that microgrids net RE generation, aggregated load and ESSs capacity are perfectly known ahead of time. Both microgrids energy cooperation and ESS can help to mitigate intermittent nature RE and thereby reduce the net energy cost. In the second method, the energy management is performed by real-time cooperation of the microgrid using two on-line algorithms of low complexity namely store-then-cooperate and cooperate-then-store. The simulation results show that the on-line algorithms perform optimal energy management very close to the off-line optimization. However, the power quality problems arise while trading/cooperation energy with the main grid.

The generic DSM model is proposed in [21] for residential users to reduce PAR, electricity bill and appliances waiting time. The GA is used for appliances scheduling while satisfying the operational constraints. There is a tradeoff between the electricity cost and the waiting time. The RTP with the IBR model is used to avoid peak formation. The results show the effectiveness of the proposed model for both single and multiple users scenarios in terms of objectives. However, they ignore the following issues: (i) user comfort and (ii) the balance between the supply and demand.

Ma *et al.* [22] introduced a novel concept of cost efficiency-based residential load scheduling framework, to improve the economic efficiency of residential sector. The cost efficient load scheduling for the demand side is performed using fractional programming, while taking into account the day ahead bidding and RTP scheme. For practical consideration, they take the service fee and DERs into account and analyze their impacts on the cost efficiency. Results show that the proposed scheduling algorithm can effectively alters users' consumption behaviors and achieve optimal cost-efficient energy consumption profile. However, user comfort is compromised while reducing the electricity cost.

Chapman *et al.* [23] presented algorithmic and strategic aspects to integrate DSM aggregation. They proposed a demand side participation (DSP) through an aggregator, which directly interacts with the EMS for load scheduling. Moreover, they have designed a generic residential demand side aggregation (RDSA) model by combining the demand side aggregation with the HEMS. The results obtained through simulations showed the effectiveness of the scheme related to reduction in electricity cost for end users and utility company. However, objectives are achieved at the cost of user comfort and PAR.

Atia *et al.* [24] presented the analysis for residential microgrids based on the sizing of RESs and battery storage systems. Mixed ILP (MILP) is used for optimal load scheduling with high penetration of RESs in residential microgrids. A stochastic model is developed for intrinsic stochastic behavior of RESs and the uncertainty involving electric load prediction. The aforementioned technique is used to increase the load flexibility, reduce computational burden and electricity cost. However, power quality problems arise with integration of RESs.

The model of DR optimization for smart home scheduling under RTP is proposed in [25]. Objective functions defined for the minimization of the electricity bill and user dissatisfaction are formulated by convex programming (CP). Regularization technique is proposed to deal with SAs for which on/off status are governed by binary decision variables. By relaxing these variables from integer to continuous values, the problem is reformulated as a new CP problem with an additional regularization term in the objectives. Simulation results show efficient reduction in electricity cost and users dissatisfaction; however, the issues of peak formation, appliances' waiting time and integration of RESs are not addressed.

An optimal energy scheduling for residential SG with centralized RESs is presented in [26]. The optimal energy scheduling aims at: (i) optimal utilization of RESs to balance the tradeoff between the system wide benefit and the associated cost due to volatility, (ii) how volatility of RESs influences its optimal use. Authors proposed special monotonic structure for load scheduling and the poly-block approximation algorithm to determine the optimal utilization of RE to lower the marginal cost. The proposed scheme optimally utilizes RESs to balance the tradeoff between benefits and cost, however, user comfort and frequency of interruption are not addressed.

Gao *et al.* [27] proposed an autonomous EMS based on game theory for residential energy management. The simulation results show that the proposed game-theoretic approach is effective in reducing the total energy cost. Zhu *et al.* [28] discussed sizing of energy storage appliances for residential feeders with high penetration of solar energy based on graphical performance. Three locations are investigated for installing energy storage devices. The rated power and storage capacity are calculated to specify the operational requirements. An EMS is proposed in [29] for optimizing the operation of the SG. Both DSM and active management schemes optimally utilize the RESs in order to reduce customers' energy consumption cost and carbon emissions.

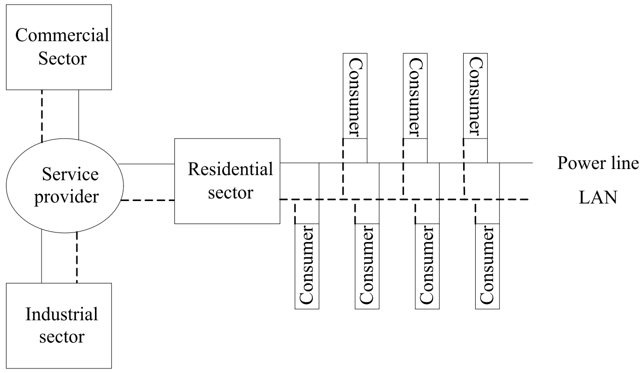

FIGURE 1. A smart power system configuration.

The efficiency of the EMS is validated on a 23-Bus 11 kV distribution network. A centralized scheduling model is proposed in [30] to exploit the demand flexibility of residential devices. Simulation results ensure that storage heaters, stationary batteries and electrical vehicles are the auspicious devices for DR.

Manzoor *et al.* [31] proposed a teacher learning based GA (TLGO) for home energy management, capable to handle a large number of parameters with less computational efforts. TLGO is able to handle complex scenarios and has high convergence rate. The related work is summarized in Table 1.

III. SYSTEM MODEL

A smart power system composed of a service provider and demand side having residential, industrial and commercial sectors containing a large number of consumers, is shown in Figure 1. We specifically focused on the residential sector and the electricity demand of the residential sector is fulfilled by the RE generation, ESS, power imported from the electricity grid station and by trading electricity among RE generating consumers.

A. HEMCS MODEL

HEMCS comprises of: EMCU, smart meter, electrical appliances and in home display and monitoring control unit (IHD and MCU) as shown in Figure 2. The EMCU receives RTP, DR and price incentive information from the utility company through a smart meter. The smart meter is one of the key factors in the SG which uses advanced metering infrastructure (AMI) that is responsible for the bi-directional communication between the electricity grid station and the consumers. The communication between the electrical appliances and the EMCU can be performed via various communication technologies such as ZigBee, Z-Wave, Wi-Fi, etc. Moreover, the smart meter receives and transmits information related to RTP, DR, price incentives and load consumption to the electricity grid station. The EMCU, based on GA, BPSO, WDO and GWDO, schedules the electrical appliances while considering an objective function, constraints and control parameters. In addition, all electrical appliances, generation

TABLE 1. An overview of the related work.

Reference(s)	Technique(s)	Objective(s)	Limitation(s)
Optimal power scheduling method for DR in HEMS [6]	GA	Minimization of electricity bill and management of PAR	The computational is high because of more scheduling time timeslots
An optimal heuristic approach utilize EMCU with rooftop photovaltiac [7]	Heuristic algorithms and MK problem (MKP)	Electricity bill and PAR minimization	User comfort is compromised
An incentive based optimal energy consumption scheduling algorithm for residential users [8]	BPSO, DR and ToU	Cost minimization	PAR, user comfort and RESs integration are ignored
IREMS for dynamic DR in smart buildings [9]	GA	Mitigation of intermittent nature of RESs and electricity cost	Energy trading between RE generating users and main grid are ignored
Two different techniques to mitigate the time varying and intermittent nature of RESs [10]	Game theoretic approach	Minimization of average cost of energy exchange within the grid	Frequency of interruption are not addressed
Power quality challenges due to integration of RESs [11]	FACTS and VSM	Mitigation of power quality issues such as voltage fluctuation, frequency fluctuation and harmonics	Cooperation between the DRESs is not considered
Real time residential side joint energy storage management and load scheduling with RESs integration [12]	Lyapunov optimization and real time algorithms	Minimize overall system cost within finite time horizon	User comfort and PAR are ignored
An intelligent MACS for energy and comfort management in smart home and sustainable buildings [13]	Heuristic algorithms	Reducing energy consumption without compromising user comfort	Minimizing PAR and demand curve smoothing are not described
Agent based control for DDSM in SG [14]	EGTTs	Peak demand reduction and efficient integration of RESs	Trading and cooperation between RE harvasting user are not mentioned
An efficient model of DSM [16]	Heuristic evolutionary approach	PAR and electricity bill reduction for residential, industrial and commercial sectors	Reduction in power consumption and pressure on the environment are ignored
Residential power scheduling for DR in SG [17]	ILP	Minimizing the tradeoff between electricity payments and discomfort	The system complexity and execution time are increased
The load scheduling and power trading in systems with high penetration of RESs [18]	Approximate dynamic programming and game theoretic approach	Electricity cost and reverse power flow reduction	Power quality issues arise due to trading excess amount of REG
Energy cooperation optimization in microgrids with RE integration [19]	Off-line optimization and on-line optimization (store-then-cooperate and cooperate-then-store)	Mitigation of intermittent nature of RESs and electricity cost	Power quality problems due cooperating/trading energy with main grid are ignored
Generic DSM model for residential users [20]	GA, combined RTP and IBR	PAR and cost minimization	Users comfort, reliability and sustainability of the grid are ignored
Novel concept of cost efficiency-based residential load scheduling framework [22]	Fractional programming while taking into account day ahead bidding process and RTP scheme	Cost minimization	User comfort is compromised
Sizing and analysis of RE and battery systems in the residential microgrids [24]	MILP and DR	Increase the load flexibility and reduce the electricity cost	User comfort is ignored
The model of DR optimization for smart home load scheduling under RTP [25]	CP and regularization techniques	Electricity bill and user dissatisfaction minimization	The issues of peak formation, number of peak power plants and integration RESs are not addressed
Optimal energy scheduling for residential SG with centralized RESs [26]	Poly-block approximation algorithm	Optimal utilization of RESs to balance the tradeoff between benefit and cost	User comfort, cooperation between RE generating user and frequency of interruption are neglected

system and control center give information to the EMCU to read and process for further action as shown in Figure 2.

B. APPLIANCES CLASSIFICATION

In this section, appliances' classification is discussed as in [15]. Appliances are classified into two categories on the bases of energy consumption pattern and their interaction with EMCU. Detailed explanation of classification is given as:

SA: This refers to the class of appliances which has wireless transceivers and a data processor to use the wireless communication technologies (i.e., ZigBee, Z-Wave and Wi-Fi) for receiving real-time data from the EMCU to control or modulate their operations. These appliances make the function faster and more energy efficient. These appliances are further classified into three types, which are discussed in the upcoming subsections.

1) POWER ELASTIC APPLIANCES

This type of appliances have elasticity in terms of their power consumption, i.e., air conditioner, water cooler and refrigerator. These appliances can operate at a minimum power during on-peak hours and at maximum power during off-peak hours in order to reduce the peak power consumption

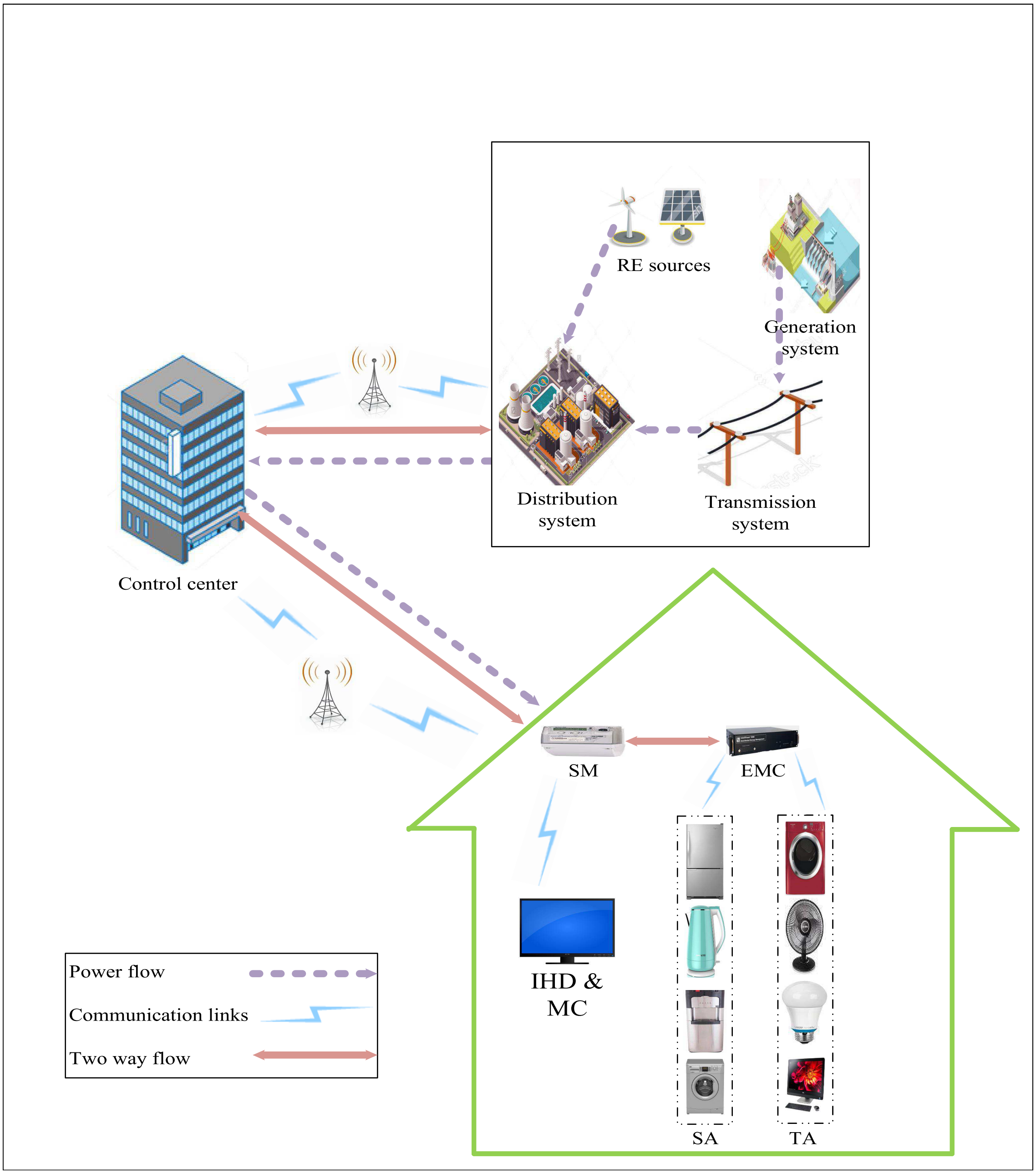

FIGURE 2. Proposed system model.

and the electricity cost. We represent such type of appliances by A^s_{pe}, their energy consumption is denoted by E^{pe}_T and p^i_r is the power rating. The energy consumption of power elastic appliances is given as follows:

$$E^{pe}_T = \sum_{i \in A^s_{pe}} \sum_{t=1}^{T} (p^i_r \times X_t) \tag{1}$$

where X_t is an indicator which indicates the status of an appliance, if it is equal to 1 the appliance will be in on state otherwise appliances will be in off state.

The daily electricity cost of power elastic appliances can be computed by the following equation:

$$C^{pe}_T = E^{pe}_T \times \varphi(t) \tag{2}$$

where C^{pe}_T denotes the total electricity cost of power elastic appliances and $\varphi(t)$ is the electricity cost per timeslot.

2) TIME ELASTIC APPLIANCES

Unlike power elastic appliances, these appliances have fixed power rating and have elasticity in their operational time. These appliances can be switched ON at any time within the user defined time intervals in order to reduce the electricity cost and PAR. In addition, these appliances can be interrupted, shifted and shutdown at any time, if needed. These appliances are capable to execute their operations at different intervals without degrading the performance of the task. For instance, a water motor, a clothes dryer and a washing machine are considered time elastic appliances. Consumers need their water tank to be full without running out of water motor or washing machine can operate on any timeslot before clothes dryer. This type of appliances is represented by A^{s}_{te} and their energy consumption is denoted by E^{te}_{T}. The energy consumption of time elastic appliances in a day is calculated as:

$$E^{te}_{T} = \sum_{i \in A^{s}_{te}} \sum_{t=1}^{T} (p^{i}_{r} \times X_t) \tag{3}$$

The daily electricity cost of time elastic appliances can be computed by the following formula:

$$C^{te}_{T} = E^{te}_{T} \times \varphi(t) \tag{4}$$

where C^{te}_{T} denotes the total electricity cost of time elastic appliances.

3) ESSENTIAL APPLIANCES

Essential appliances, such as an electric kettle, an electric iron and an oven have fixed power ratings. These appliances cannot be interrupted once they start their operations until completion of their tasks. They can only be shifted before they are turned ON. These appliances have predefined scheduling time horizon in which they operate in order to enhance users' comfort. It is represented by A^{s}_{ea}, having a power rating p^{i}_{r} and the net energy consumption E^{ea}_{T}. A daily energy consumption of these appliances is calculated as:

$$E^{ea}_{T} = \sum_{i \in A^{s}_{ea}} \sum_{t=1}^{T} (p^{i}_{r} \times X_t) \tag{5}$$

The electricity cost can be calculated by the following Equation:

$$C^{ea}_{T} = E^{ea}_{T} \times \varphi(t) \tag{6}$$

where C^{ea}_{T} denotes the electricity cost of the energy consumed by the essential appliances.

TA: Unlike SA, TA refers to the type of appliances which can be operated and controlled manually without any interaction to the EMCU. These appliances are used by the consumers manually if needed such as, an electric bulb, a fan, a television, a computer etc. A TA cannot be scheduled, because they do not communicate and interact with the EMCU.

C. POWER USAGE AND CONSUMPTION MODEL

Let the set of all appliances denoted by $A^{t}_{n} = \{SA \cup TA\}$ such that, $SA = \{A^{s}_{pe} \cup A^{s}_{te} \cup A^{s}_{ea}\}$ and $TA = \{fan, television, computer\}$. Moreover, $A^{s}_{pe} = \{AC, WC, RF\}$, $A^{s}_{te} = \{WM, CD, Wm\}$ and $A^{s}_{ea} = \{EK, EI, OV\}$ are sets of power elastic, time elastic and essential appliances, respectively. The scheduling time horizon is of 24 hours and every hour represents the timeslot of 12 minutes. In other words every hour has 5 timeslots and the total timeslots are120. The daily scheduling time horizon is represented by the symbol $T_h = \{1, 2, 3, \ldots\ldots, T\}$ and $1, 2, 3, \ldots\ldots, T$ represents the day timeslots from 1 to 120. For each electrical appliance i, the energy consumption at each timeslot t, is given as follow:

$$E^{i}_{c}(t) = \{E^{i}_{c}(1), E^{i}_{c}(2), E^{i}_{c}(3), \ldots\ldots, E^{i}_{c}(T)\} \tag{7}$$

where $E^{i}_{c}(1), E^{i}_{c}(2), E^{i}_{c}(3), \ldots\ldots, E^{i}_{c}(T)$ denote the energy consumption of each electrical appliance i, at each timeslot t, during a scheduling time horizon. The daily aggregated energy consumption of each electrical appliance i, is given below:

$$E^{i}_{T} = \sum_{t=1}^{T} E^{i}_{c}(t) \tag{8}$$

where E^{i}_{T} denotes the aggregated energy consumption.

D. PRICING MODEL

To compute the electricity cost, a variety of pricing models are available, i.e., ToU, critical peak rebates (CPR), RTP and critical peak pricing (CPP). When only the RTP is used, there is a possibility of building peaks during OFF peak hours, because most users would shift their loads to off peak hours for managing the electricity consumption cost and as a result the entire electricity power system is damaged. Therefore, we combined the RTP and IBR schemes in our proposed scheduling strategy to effectively reduce the electricity cost, peak power consumption and enhance the reliability of the power system. This combined pricing model is beneficial for both utility and consumers. For instance, consumers want to reduce the electricity cost and schedule most of their appliances during timeslots 0-30 (12am-6am) due to low EP which may result in peak formation during this interval. To avoid this peak formation, IBR is incorporated. In this pricing model, when the load of a consumer increases over a certain threshold, a penalty is added to the consumers' bill which decreases the peak formation. The combined RTP and IBR function is defined as follows:

$$RPI(E) = \begin{cases} \varphi(t) & \text{if } 0 \le E^{i}_{T} \le E_{th} \\ \kappa \times \varphi(t) & \text{if } E^{i}_{T} \ge E_{th} \end{cases} \tag{9}$$

where E^{i}_{T} denotes the appliances' aggregated energy consumption, E_{th} is the threshold of enregy consumption and whenever aggregated energy consumption exceeds the threshold, the electricity cost increases by a constant positive value κ.

E. RE INTEGRATION MODEL

Greening the power system aims at integration of RESs on a large scale. RESs integration is a practice of developing efficient ways to deliver the RE to the grid and neighboring consumers at the time of need to enhance the revenue and reliability of the power system. Whereas, the intermittent nature of RESs, which creates fluctuation in the power generation, makes them inefficient. Integration of te ESS is an efficient way to smooth out these fluctuations. The alternative way is trading where surplus generation is distributed among neighboring consumers. On the basis of RESs generation and energy trading, residential consumers are divided into three categories [15]: GEC, SEC and TEC, where GEC gets energy only from the electricity grid station and neither cooperates nor generates their own energy as shown in Figure 3. The SEC generates its own energy, as well as takes energy from the electricity grid station and neighboring RE generating consumers to fulfill their electricity demand. Unlike the SEC, the TEC generates, stores and trades its energy with other consumers. The detailed description is as follows:

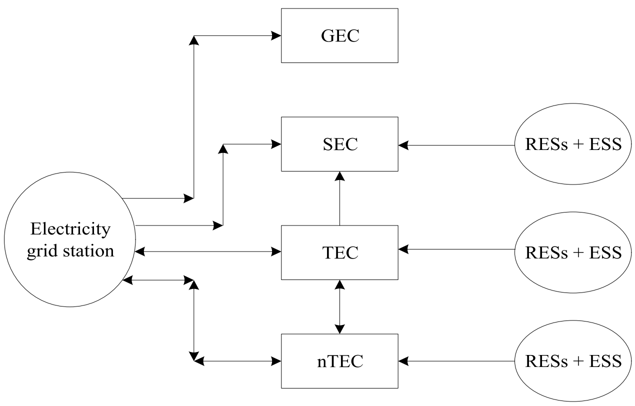

FIGURE 3. **Proposed RE model.**

1) GEC

The GEC depends only on grid energy, it does not have RESs. The energy demand of GEC is $D_g(t)$ units per timeslot. The energy demand of GEC is bounded as $D_g(t) \leq D_{gmax}$. The GEC uses the RTP and the price incentive information in order to take part in a DR program to reduce the electricity cost and the peak power consumption by shifting their load from on peak hours to off peak hours. The aggregated energy consumption of GEC can be calculated by the following formula:

$$E_g = \sum_{t=1}^{T} E_g(t) \tag{10}$$

2) SEC

The SEC fulfills its energy demand from RESs, ESS, neighboring RE generating consumers and electricity grid station. The energy demand of SEC per timeslot is $D_s(t)$ units. The energy demand per timeslot should not exceed the maximum demand $D_s(t) \leq D_{smax}$. The SEC fulfills its demand by its own RE. If the demand of SEC increases, the available energy from RESs $R_s(t) < D_s(t)$, they utilize the available energy and the rest of the demand will be called unsatisfied demand as:

$$D_s(t) - R_s(t) = D_s^u(t) \tag{11}$$

The SEC fulfills the unsatisfied demand by the following manner:

1) Draws energy stored from the ESS
The SEC draws $B_{d,s}^e(t)$ units of energy from its ESS to serve the unsatisfied demand.
2) Borrows the energy from the neighboring TEC
The SEC takes the surplus energy of $R_{s,T}(t)$ units from the TEC in order to fulfill the unsatisfied demand.
3) Transfers the energy from the electricity grid station
In this case, the energy drawn from the ESS and borrowed from the TEC is insufficient to satisfy the residual demand, then the SEC gets $E_g(t)$ units of energy from the electricity grid station.

The sum of the energy drawn from the ESS, energy transferred from the TEC and energy transferred from the electricity grid station must satisfy the residual demand as mentioned in the Equation below:

$$B_{d,s}^e(t) + \sum_{t=1}^{T} R_{s,T}(t) + E_g(t) = D_s^u(t)$$

$$\sum_{t=1}^{T} R_s(t) + B_{d,s}^e(t) + \sum_{t=1}^{T} R_{s,T}(t) + E_g(t) = D_s(t) \tag{12}$$

When harvested energy from RESs exceeds the demand $R_s(t) > D_s(t)$ then the SEC performs the following actions:

1) The excess energy is stored in the ESS to facilitate the energy efficient integration of RESs. The storing energy in the ESS is bounded by $S_{b,s}^{e,\min} \leq S_{b,s}^e(t) \leq S_{b,s}^{e,\max}$.
2) Stops borrowing energy from the neighboring TEC.
3) Stops getting energy from the electricity grid station.

where $E_g(t)$ is the energy taken at each timeslot from the electricity grid station, $R_{s,T}$ is the electricity bought at each timeslot from the neighboring TEC, $R_s(t)$ is the RE harvested at each timeslot from RESs, $S_{b,s}^e(t)$ is the initially stored energy in the ESS of the SEC.

3) TEC

The TEC fulfills its energy demand from the RESs, ESS, utility and the neighboring TEC, it also trades with other users and the grid. The energy demand of the TEC is $D_T(t)$ and bounded by $D_T(t) \leq D_{tmax}$. The TEC fulfills its energy demand and trades energy in the following manner. If the harvested energy is deficient, $R_T(t) < D_T(t)$ then unsatisfied demand is calculated as:

$$D_T(t) - R_T(t) = D_T^u(t) \tag{13}$$

1) Draw energy stored from the ESS
The TEC uses $B_{d,T}^e(t)$ units of energy from the ESS in order to fulfill the demand of the unsatisfied load.

2) Exchange energy among the TEC
The TEC can borrow $R_{T,n}(t)$ from the neighboring TEC to fulfill the residual load.
3) Transfers energy from the electricity grid station
In this case, the energy from the ESS and the energy borrowed from the TEC is the insufficient to meet the demand, then the TEC borrows $E_g(t)$ units of energy from the electricity grid station.

The unsatisfied demand is equal to the sum of energy taken from the ESS, neighboring TEC and electricity grid station as shown in the following Equation:

$$B^e_{d,T}(t) + \sum_{t=1}^{T} R_{T,n}(t) + E_g(t) = D^u_T(t)$$

$$\sum_{t=1}^{T} R_T(t) + B^e_{d,T}(t) + \sum_{t=1}^{T} R_{T,n}(t) + E_g(t) = D_T(t) \quad (14)$$

where $D^u_T(t)$ shows the unsatisfied demand of the TEC, $R_{T,n}(t)$ is the energy exchange among the TEC and $B^e_{d,T}(t)$ is the energy drawn from the ESS. In the case, when the harvested energy exceeds the demand $R_T(t) > D_T(t)$, the surplus energy is stored in the ESS or traded with other consumers or the grid to utilize the energy efficiently and increase the revenue.

F. ESS MODEL

The ESS is used to tackle the fluctuations in the RE generation and to efficiently utilize the RE and enhance the reliability of the power system. The SEC and TEC have the ESS installed in their premises in order to facilitate energy efficient integration of RESs. The modeling of the ESS for the SEC and the TEC is as follow:

1) SEC, ESS MODEL

The ESS greatly contributes in energy efficient integration of RESs, it also increases safety, reliability and assists in eco-friendly environment. Our proposed energy model for the ESS at the SEC premises evolves as:

$$S^e_{b,s}(t+1) = S^e_{b,s}(t) - B^e_{d,s}(t) + S^e_s(t) \quad (15)$$

where $S^e_{b,s}(t)$ is the initially stored energy in the ESS, $S^e_s(t)$ is the amount of energy stored in the ESS at each timeslot and $B^e_{d,s}(t)$ is the unit of energy drawn from the ESS. The energy availability constraints of the ESS are as follows:

$$B^e_{d,s}(t) \leq S^e_{b,s}(t) \quad (16)$$

We impose charging, discharging and finite battery capacity constraints at each timeslot as:

$$\begin{aligned} B^e_{d,s}(t) &\leq S^{e,\min}_{b,s} \\ S^{e,\max}_{b,s} &\geq 0 \& S^{e,\min}_{b,s} \geq 0 \\ S^{e,\min}_{b,s} &\leq S^e_{b,s}(t) \leq S^{e,\max}_{b,s} \end{aligned} \quad (17)$$

where $S^{e,\min}_{b,s}$ is the minimum limit of battery discharge, finite capacity or maximum limit for charging of battery is denoted by $S^{e,\max}_{b,s}$. The practical assumption on capacity of the ESS is given below:

$$S^{e,\max}_{b,s} \geq B^{e,\max}_{d,s} + S^{e,\min}_{b,s} \quad (18)$$

where the maximum energy that can be drawn from the ESS is denoted by $B^{e,\max}_{d,s}$.

2) TEC, ESS MODEL

The TEC installs the ESS to store the harvested energy and overcome the fluctuation problems in the RE it also facilitates the energy efficient integration of RESs in order to increase the revenue and eliminates the wastage of energy. The ESS charging evolves as:

$$S^e_{b,T}(t+1) = S^e_{b,T}(t) - B^e_{d,T}(t) + S^e_T(t) \quad (19)$$

where $S^e_{b,T}(t)$ is the initially stored energy in the ES, $S^e_T(t)$ is the amount of energy stored in the ESS at each timeslot t and $B^e_{d,T}(t)$ units of energy is drawn from the ESS. The energy availability constraints of the TEC and the ESS is as follows:

$$B^e_{d,T}(t) \leq S^e_{b,T}(t) \quad (20)$$

The charging and discharging of the ESS are bounded by the upper limit and lower limit as follows:

$$\begin{aligned} B^e_{d,T}(t) &\leq S^{e,\min}_{b,T} \\ S^{e,\max}_{b,T} &\geq 0 \& S^{e,\min}_{b,T} \geq 0 \\ S^{e,\min}_{b,T} &\leq S^e_{b,T}(t) \leq S^{e,\max}_{b,T} \end{aligned} \quad (21)$$

where $S^{e,\min}_{b,T}$ is the lower limit of the battery discharge, the finite capacity or upper limit for charging is denoted by $S^{e,\max}_{b,T}$ and the battery charging and discharging of the ESS at each timeslot is bounded in between these two limits. The practical assumption on the capacity of the ESS is given as:

$$S^{e,\max}_{b,T} \geq B^{e,\max}_{d,T} + S^{e,\min}_{b,T} \quad (22)$$

where $B^{e,\max}_{d,T}$ denotes the maximum energy that can be drawn from the ESS of the TEC.

IV. PROBLEM FORMULATION

In this section, the load scheduling and the RE integration problem is formulated. In general, it is difficult to formulate and solve the joint optimization problem of the load scheduling and the RE integration; therefore, we formulate them individually.

A. SCHEDULING PROBLEM FORMULATION

The load scheduling problem is formulated by multiple knapsack approach. The knapsack problem is a combinatorial problem (finding an optimal solution from a finite set of objects), where multiple objects are associated with a value and weight [32]. The object must be packed such that the value of the object within the knapsack is maximized and weight must be in predefined limit. The knapsack has n objects; each object i from the set of n objects has two attributes: value and weight along with the constraint of the capacity to denote the minimum and maximum weights that can be easily supported by the knapsack. The knapsack problem is a standard problem template which is used to map numerous problems in multiple domains.

1) MAPPING SCHEDULING PROBLEM TO KNAPSACK

The mapping of scheduling problem to knapsack problem is outlined as:

- The m knapsacks correspond to timeslots T_h
- The n objects show n appliances to be packed.
- The weight of each object represents the energy consumed $E_c^i t$ by each appliance in each timeslot.
- The value of object is cost.
- The capacity is the weight which knapsack supports, it depicts the amount of electricity which can be acquired from the electricity grid station at a given timeslot. On the consumers' side the electricity cost and the peak power consumption can be controlled in order to ensure that the utility is not overstressed.

Now we provide the mathematical model for our scheduling problem considering electrical appliances, objective function and constraints using knapsack.

For SA, we define $S_t^{sa} = (r_t^n, w_t^n)$ state of the SA at each timeslot, where r_t^n indicates the number of the remaining timeslots of the SA, w_t^n shows the number of waiting timeslots for which the operation of the appliance can be delayed; where $X_t \in \{0, 1\}$ is an indicator, for on and off status of appliances. Power elastic appliances A_{pe}^s, start operating immediately and show elasticity in their power in order to achieve the desired objectives. The mathematical model for the state of power elastic appliances is as follows:

$$\begin{aligned} S_t^{pe} &= (T_s^o, 0) \\ S_{t+1}^{pe} &= \begin{cases} (r_t^n - 1, 0) & \text{if } X_t = 1,\ r_t^n \geq 1 \\ (0, 0) & \text{otherwise} \end{cases} \end{aligned} \tag{23}$$

where Equation 23 indicates the current state and state in the next timeslot of power elastic appliances. The time elastic appliances A_{te}^s, operation can be delayed and interrupted if required. The mathematical model for the state of time elastic appliances is given by:

$$\begin{aligned} S_t^{te} &= (T_s^o, \beta - \alpha - T_s^o + 1) \\ S_{t+1}^{te} &= \begin{cases} (r_t^n, w_t^n - 1) & \text{if } X_t = 0,\ w_t^n \geq 1 \\ (r_t^n - 1, w_t^n) & \text{if } X_t = 1,\ r_t^n \geq 1 \end{cases} \end{aligned} \tag{24}$$

Equation 24 ensures the initial and the next timeslot status of A_{te}^s.

Essential appliances A_{ea}^s, tolerate delay before starting their operations. The state of essential appliances is mathematically modeled as:

$$\begin{aligned} S_t^{ea} &= (T_s^o, \beta - \alpha - T_s^o + 1) \\ S_{t+1}^{ea} &= \begin{cases} (r_t^n, w_t^n - 1) & \text{if } X_t = 0,\ w_t^n \geq 1 \\ (r_t^n - 1, 0) & \text{if } X_t = 1,\ r_t^n \geq 1 \end{cases} \end{aligned} \tag{25}$$

where Equation 25 shows current and next timeslot states of essential appliances. In the scheduling problem, our objectives are to minimize the electricity cost, the PAR and the tradeoff between the electricity cost and the user comfort. The objective function subjected to constraints is formulated using knapsack as follows:

$$\min \mathrm{F}(C_T^e, A_r^p, C_w) \tag{26}$$

where

$$\begin{aligned} C_T^e &= \sum_{i \in SA} p_r^i \sum_{t=1}^{T} (X_t \times \varphi(t)) \\ \text{Peak} &= \max(\sum_{i \in SA} (p_r^i \times X_t)) \\ \text{Average} &= \frac{1}{T} (\sum_{i \in SA} \sum_{t=1}^{T} (p_r^i \times X_t)) \\ A_r^p &= \frac{\text{Peak}}{\text{Average}} \\ C_w &= \begin{cases} \mu \times t \times (T_s^o - A_i) & \text{for } T_s^o \geq A_i \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

subjected to:

$$\sum_{i \in SA} (E_c^i(t) \times X_t) \leq Capacity \tag{27a}$$

$$Capacity - \sum_{i \in SA} (E_c^i(t) \times X_t) \geq 0 \tag{27b}$$

$$\sum_{i \in SA} E_c^{i,\text{unsch}}(t) = \sum_{i \in SA} E_c^{i,\text{sch}}(t) \tag{27c}$$

$$\sum_{i \in SA} C_T^{e,\text{un-sch}} \geq \sum_{i \in SA} C_T^{e,\text{sch}} \tag{27d}$$

$$\sum_{i \in SA} T_s^{o,i,\text{unsch}} = \sum_{i \in SA} T_s^{o,i,\text{sch}} \tag{27e}$$

$$X_t^{\text{un-sch}} \neq X_t^{\text{sch}} \tag{27f}$$

The constraints in Equations 27a and 27b ensure that the aggregated energy consumptions of all set of appliances should not exceeds the load capacity of the electricity grid station. Total energy consumption before and after scheduling must remain constant as indicated by the constraint in Equation 27c. Equation 27d indicates that our scheme performs well in terms of electricity cost. Equation 27e ensures that the total operational time of all appliances before and after scheduling is equal. The status of appliances before and after scheduling will not be the same which ensures that appliances are scheduled properly as indicated by Equation 27f.

B. COST MODEL AND TRADING PROBLEM FORMULATION

The ESS and trading among consumers facilitates the energy efficient integration of the RESs. Therefore, we formulate the trading and the cost model for energy transferred from the neighboring TEC and the electricity grid station. For transferring the energy from the TEC to the SEC, the cost of per unit energy transfer is denoted as $C^{e}_{s,T}(t)$. Similarly, the electricity cost per unit of the energy exchange among the neighboring TEC during any timeslot t, is $C^{e}_{T,n}(t)$ and the cost of energy transfer from the electricity grid station to consumers is $C^{e}_{g}(t)$. The objective function of the net cost of the energy transfer of the aforementioned three consumers, is modeled as follows:

$$\mathrm{Cost} = \min\left(\mathrm{Cost}_{\mathrm{GEC}}, \mathrm{Cost}_{\mathrm{SEC}}, \mathrm{Cost}_{\mathrm{TEC}}\right) \tag{28}$$

where

$$\mathrm{Cost}_{\mathrm{GEC}} = \sum_{t=1}^{T} C^{e}_{g}(t) \times E_{g}(t)$$

$$\mathrm{Cost}_{\mathrm{SEC}} = C^{e}_{g}(t) \times E_{g}(t) + \sum_{t=1}^{T} C^{e}_{s,T}(t) \times R_{s,T}(t)$$

$$\mathrm{Cost}_{\mathrm{TEC}} = C^{e}_{g}(t) \times E_{g}(t) + \sum_{t=1}^{T} C^{e}_{T,n}(t) \times R_{T,n}(t)$$

The objective of the controller is to design and tune the system control parameters such that, the cost of energy transfer and the reverse power flow are minimized, subject to consumers' trading and ESS constraints are as follow:

$$\text{subject to: } C^{r}_{s,T}(t) < v\, C^{e}_{g}(t) \,\&\, C^{r}_{T,n}(t) < C^{e}_{g}(t) \tag{29a}$$

$$C^{e}_{g}(t) \le C^{e,\max}_{g} \,\&\, C^{r}_{s,T}(t) \le C^{r,\max}_{s,T} \tag{29b}$$

$$B^{e}_{d,s}(t) + \sum_{t=1}^{T} R_{s,T}(t) + E_{g}(t) = D^{u}_{s}(t) \tag{29c}$$

$$B^{e}_{d,T}(t) + \sum_{t=1}^{T} R_{T,n}(t) + E_{g}(t) = D^{u}_{T}(t) \tag{29d}$$

$$S^{e}_{s}(t) \le R_{s}(t) \tag{29e}$$

$$S^{e}_{T}(t) + \sum_{t=1}^{T} R_{s,T}(t) \le R_{T}(t) \tag{29f}$$

$$S^{e}_{b,s}(t+1) = S^{e}_{b,s}(t) - \sum_{t=1}^{T} B^{e}_{d,s}(t) + S^{e}_{s}(t) \tag{29g}$$

$$S^{e}_{b,T}(t+1) = S^{e}_{b,T}(t) - \sum_{t=1}^{T} B^{e}_{d,T}(t) + S^{e}_{T}(t) \tag{29h}$$

$$B^{e}_{d,s}(t) \le \min(S^{e}_{b,s}(t), S^{e,\min}_{s}) \tag{29i}$$

$$B^{e}_{d,T}(t) \le \min(S^{e}_{b,T}(t), S^{e,\min}_{T}) \tag{29j}$$

$$S^{e}_{s}(t) \le \min(S^{e,\max}_{b,s} - S^{e}_{b,T}(t), S^{e,\max}_{s}) \tag{29k}$$

$$S^{e}_{T}(t) \le \min(S^{e,\max}_{b,T} - S^{e}_{b,T}(t), S^{e,\max}_{T}) \tag{29l}$$

The cost of energy transfer from the TEC and the electricity grid station is bounded as in Equation 29a and Equation 29b. Equation 29c and Equation 29d show the residual demand of both the SEC and the TEC, it will be met under the objective function. In case of surplus energy, an amount of energy stored in its own battery and an amount of energy donated to neighboring consumers will be less than the energy harvested by consumers as in Equation 29e and Equation 29f. Equation 29g and Equation 29h ensure the storing capability of the ESS of the SEC and the TEC, respectively. The energy drawn from the ESS of SEC and TEC at each timeslot is bounded as shown in Equation 29i and 29j. The energy stored in the ESS of the SEC and the TEC in each timeslot is bounded as shown in Equation 29k and Equation 29l.

TABLE 2. Description of single household.

Type	SA	OTS	Power rating (KW)
Power elastic	Air conditioner	75	[0.8 1.5]
	Refrigerator	70	[0.5 1]
	Water cooler	60	[0.18 0.5]
Time elastic	Washing machine	40	0.7
	Clothes dryer	40	2
	Water motor	36	0.8
Essential	Electric kettle	20	1.5
	Electric iron	30	1.8
	Oven	25	2

V. SIMULATION RESULTS AND DISCUSSION

In this section, we present the simulation results to highlight the effectiveness and productiveness of our proposed technique in terms of electricity consumption cost, PAR and to balance the tradeoff between the cost and the user comfort. Different simulations are performed, then we show the results of average of 10 runs. Furthermore, the control parameters for performing simulations are: the 24 hours time horizon which is distributed over 120 timeslots by making each scheduling slot of 12 minutes. A daily scheduling time horizon is represented by the symbol $T_h = \{1, 2, ..., T\}$ and $1, 2, ..., T$ represents the timeslots from 1 to 120. The RTP signal is midwest independent system operator (MISO) daily EP tariff taken from the federal energy regulatory commission (FERC) as illsutrated in Figure 4 [33]. From the RTP signal, it is clear that the timeslots 30-45 (6am-9am) and 85-100 (5pm-8pm) are on peak slots, timeslots 50-70 (10am-2pm) are shoulder peak and the rest of the timeslots are off peak as depicted in Figure 4.

The combined RTP and IBR is exploited for encouraging users to schedule appliances' from on peak to off peak hours to reduce the electricity cost. We assume that the EMCU receives RTP, DR and price incentive information from the utility company via the SM and keeps in view the objective function, constraints, control parameters and user behavior to schedule the SA for a single home and multiple homes [27]. For this reason users set some control parameters for the SA such as, scheduling time horizon, operation timeslots (OTS), start time of interval α, end time of interval β and power rating as listed in Table 2. The control parameters can be set on the IHD and the MCU and transmitted to the EMCU for further processing. The control parameters for multiple homes are listed in Table 3. We have performed comparative evaluation of heuristic techniques by scheduling the SA, evaluation is

TABLE 3. Multiple homes appliances description.

Category	SA	Mode1 OTS	Mode2 OTS	Mode3 OTS	Mode1 power (KW)	Mode2 power (KW)	Mode3 power (KW)
Power elastic	Air conditioner	75	55	45	[0.8 1]	[1 1.5]	[0.8 1.5]
	Water cooler	70	50	40	[0.01 0.5]	[0.5 1]	[0.01 1]
	Refrigerator	60	40	30	[0.18 0.5]	[0.5 1]	[0.18 1]
Time elastic	Washing machine	40	20	10	0.38	0.5	0.7
	Clothes dryer	40	20	10	0.8	2	3
	Water motor	36	16	6	0.8	1	1.2
Essential	Electric kettle	20	10	5	1.2	1.5	3
	Electric iron	30	10	5	1	1.1	1.8
	Oven	25	15	5	2	2.15	2.4

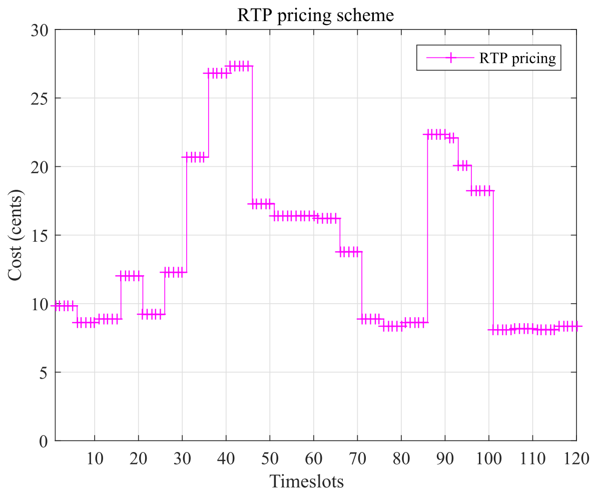

FIGURE 4. RTP signal.

based on performance parameters: minimize the electricity cost, PAR and user comfort. The energy efficient integration of RESs is facilitated by ESS and trading energy among consumers in order to reduce the cost and reverse the power flow. The detailed description is as follow:

A. FEASIBLE REGION

The area which satisfy all linear constraints based on the defined objective function is called the feasible region. The region satisfies all restrictions imposed by inequality constraints and none of them is violated. The solution fond by the objective function within this region will be a feasible solution.

1) ELECTRICITY COST AND CONSUMPTION

We find a feasible region for cost and energy consumptions in order to set boundaries for our objective function. For this purpose, we consider a cost ranging from 0.081 to 2.1 cents/kWh and a range of power consumption is from 1 to 9.1 kWh as constraints. The feasible region is based on the coordinates and conditions listed in Table 4. These coordinates will set the constraints as demonstrated below, which bound scheduled load and electricity cost with in the feasible region.

$$0.081 \leq C^i(t) \leq 2.1 \qquad \text{(C1)}$$

$$1 \leq E^i_c(t) \leq 9.1 \qquad \text{(C2)}$$

TABLE 4. Conditions for feasible region.

Conditions	Electricity cost (cents)
Min. power, Min. price	0.081
Min. power, Max. price	0.27
Max. power, Min. price	0.74
Max. power, Max. price	2.50

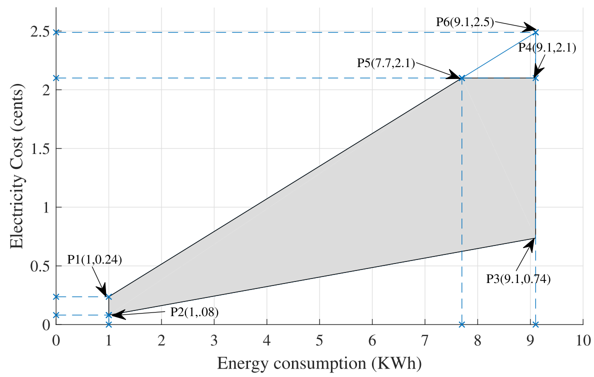

FIGURE 5. Electricity cost vs. energy consumption.

where constraint C1 represents that the maximum cost at any timeslot is 2.1 cents, which ensures that scheduled cost should remain under 2.1 cents at any timeslot. The energy consumption of the scheduled load must remain within the range indicated by constraint C2. The net energy consumption of all set of appliances should not exceed electricity capacity of grid station. The aggregated electricity cost is enclosed by the coordinates P1, P2, P3 and P6 as shown in Figure 5. Whereas, the feasible region is bounded by the coordinates P1, P2, P3, P4 and P5. The cost lies at any timeslot within this region that is feasible.

2) ELECTRICITY COST AND WAITING TIME

When the waiting time is zero then the electricity cost is maximum and vice versa. Thus, these parameters are inversely proportional to each other. The range of delay which our system can tolerate is 0-10 timeslots, the electricity cost sets the coordinate with respect to the waiting time listed in Table 5. The region encircled by coordinates P1, P2 and P3 is the feasible region, any solution within this region is feasible. Where P1 ensures that, when users do not wait, they pay more. When users can tolerate delay, the electricity cost

TABLE 5. Coordinates of feasible region.

Case	Coordinates
Min. waiting time, cost	P1 (0 78)
Avg. waiting time, cost	P2 (5 41)
Max. waiting time, cost	P3 (10 39)

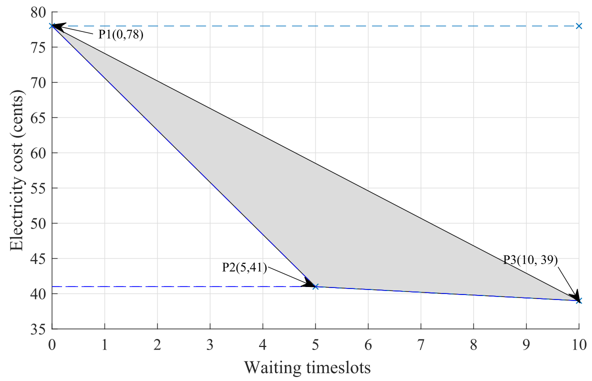

FIGURE 6. Electricity cost vs. waiting time.

decreases with respect to the waiting time as indicated by coordinates P2 and P3 of the feasible region. The coordinates set constraints, which define boundaries of the feasible region as shown in Figure 6. The enclosed region is the feasible region based on points P1-P3 and any solution within this region is acceptable.

$$0 \leq w_t^n \leq 10 \tag{C3}$$

$$0 \leq C_T^e \leq 78 \tag{C4}$$

where constraint C3 ensures that the waiting time of the scheduled load must be between 0 and 10 timeslots. Aggregated electricity cost of the scheduled load must be within the boundaries of the feasible region as indicated by constraint C4.

B. ELECTRICITY COST ANALYSIS FOR DIFFERENT SCHEDULING SCHEMES

The daily electricity cost of unscheduled and scheduled loads for a single home and multiple homes is depicted in Figure 7. The unscheduled electricity load cost is high during the timeslots 30-45 (6am-9am) and 85-100 (5pm-8pm), because consumers use more appliances in these timeslots that tend to lead to high electricity cost of 2.1 cents and 1.4 cents. The meta-heuristic (GA, BPSO, WDO, and GWDO) based scheduling reduces the electricity consumption cost up to 0.7, 0.65, 0.67 and 0.60 cents, respectively. The maximum daily electricity bill per timeslot is reduced from 2.1 cents to 0.6 cents with GWDO, that is 71.4% reduction. Our proposed the GWDO algrithm outperforms other scheduling algorithms as shown in Figure 7a. The results show that the GWDO algorithm is more stable. The electricity cost analysis of five homes is illustrated in Figure 7b. We analyze the consumption cost of electricity profile of different homes while considering dynamic OTS and power rating of appliances for each home. The scheduling of appliances through optimization techniques helped in reducing the PAR and electricity cost. Extensive simulations show the significant reduction in electricity cost when using the GWDO algorithm compared to heuristic techniques.

C. PEAK POWER CONSUMPTION ANALYSIS FOR DIFFERENT HEURISTIC BASED EMCU

The daily power consumption profiles of unscheduled and scheduled loads based on GA, BPSO, WDO and our proposed (GWDO) for a single households and multiple household are depicted via Figure 8. The power consumption of unscheduled appliances is high during the timeslots 30-45 (6am-9am) and timeslots 85-100 (5pm-8pm), because consumers do more activities in these time slots, that results in high electricity cost and PAR. The EMCU based on GA, BPSO, WDO and GWDO schedules household appliances while considering objective function, user defined constraints, combined pricing schemes and control parameters in order to reduce the electricity cost, PAR and waiting times. It can be seen from Figure 8a, that the peak power consumption of unscheduled appliances is relatively more due to the dynamic operation and without taking into consideration the EP that eventually lead to more peak power consumption and electricity cost. However, the scheduled load must be within the bounds defined by the feasible region as shown in Figure 5. On the other hand, the electricity cost and peak power consumption are relatively less using optimization techniques (GA, BPSO, WDO and GWDO) and considering various factors (EP, on/off peak timeslots and user preference). The peak power consumption of unscheduled loads is 9KW and by the scheduled load: GA, BPSO, WDO and GWDO is 7 kW, 6.3 kW, 6.1 kW and 5.9 kW, respectively. The GA schedules time elastic appliances during timeslots where the EP is low. The BPSO scheduler shifts appliances from on peak timeslots 30-45 (6am-9am) to off peak timeslots 10-25 (2am-5am). The results show that our proposed GWDO has more suitable, stable and optimal load profile than unscheduled and scheduled loads using other techniques, because GWDO employs properties of both GA and WDO to properly tune the control parameters. The decrement percentage between unscheduled and scheduled loads is listed in Table 6. The load profile of five homes is shown in Figure 8b. We take dynamic OTS and power ratings and evaluate the performance of the GA, BPSO, WDO and GWDO. We take dyamic OTS and power ratings, because in different home users behavior and appliances are different. The heuristic based EMCU efficiently schedules appliances, while considering objective functions, stochastic behavior of users, constraints and control parameters for minimizing the PAR and the electricity consumption cost. Additionally, our proposed GWDO outperforms other heuristic techniques as shown in Figure 8b.

D. TRADEOFF ANALYSIS OF ELECTRICITY COST AND USER COMFORT

User comfort is related to both electricity cost and appliances waiting time. The appliances scheduled by the GA, BPSO,

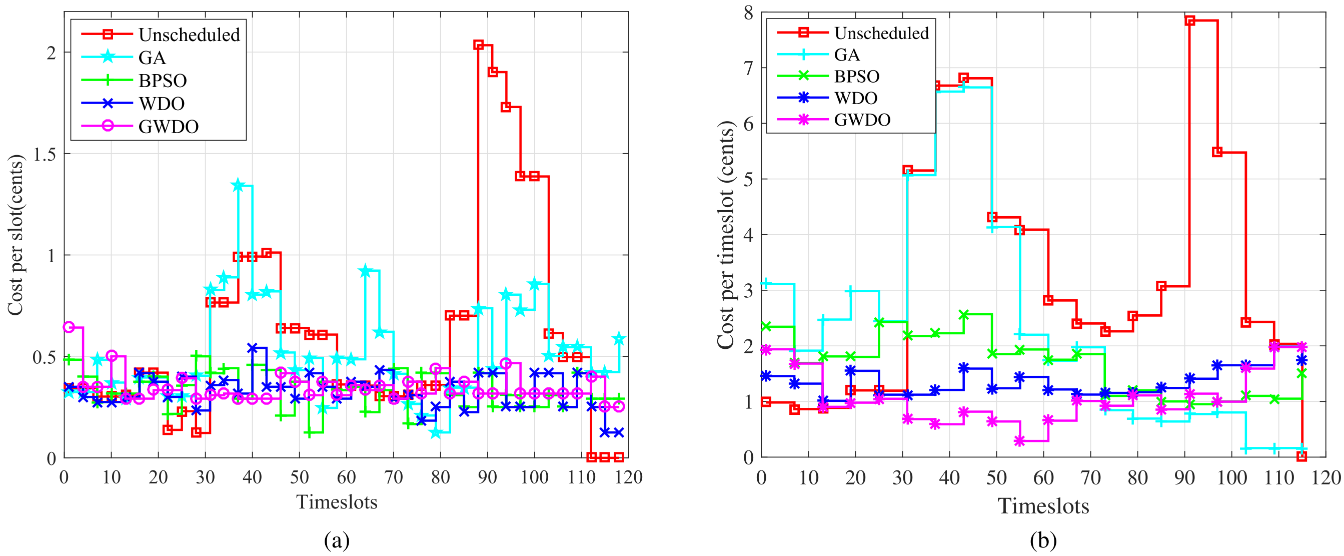

FIGURE 7. Electricity cost per timeslot. (a) Single home. (b) Multiple homes.

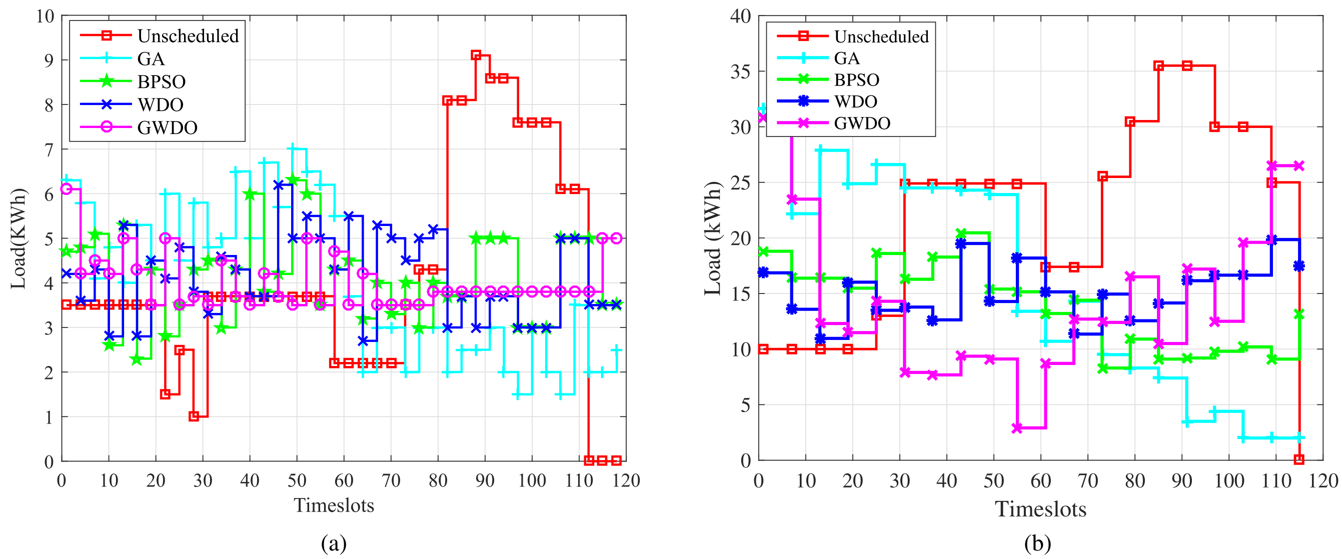

FIGURE 8. Energy consumption profile. (a) Single home. (b) Multiple homes.

TABLE 6. Peak power consumption analysis.

Techniques	Peak load	Difference	Percent decrement (%)
Unscheduled	9	-	-
BPSO	6.3	2.7	30
WDO	6.1	2.9	32
GA	7	2	22.3
GWDO	5.9	3.1	34

WDO and GWDO lead towards low electricity cost as compared to unscheduled load case, because heuristic techniques are applied keeping in view the objective function, constraints and control parameters. Generally, electricity cost and appliances' waiting time are inversely related. Heuristic based EMCU try to balance the tradeoff between the electricity cost and the user comfort. In addition, by including the user comfort constraints on the objective function, the performance of heuristic techniques (GA, BPSO, WDO and GWDO) is enhanced in terms of user comfort and electricity cost. For a single home and multiple homes, the electricity cost is high if appliances waiting time is zero and low if appliances waiting time is greater than zero as shown in Figure 9a and Figure 9b.

E. PAR PERFORMANCE ANALYSIS

The relationship between the unscheduled and scheduled loads with respect to the PAR for a single home and multiple homes is shown in Figure 10. The PAR minimization emphasizes on the balanced energy consumption in all timeslots. The EMCU reduces the PAR using DR incentive, combined

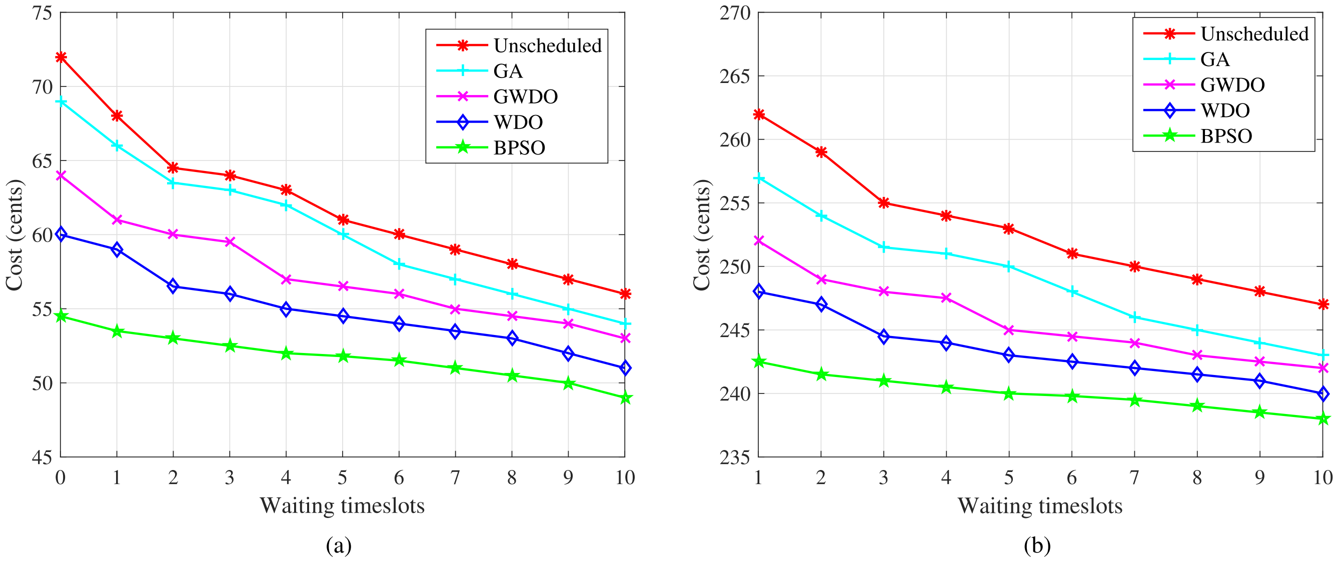

FIGURE 9. Electricity cost and user comfort tradeoff. (a) Single home. (b) Multiple homes.

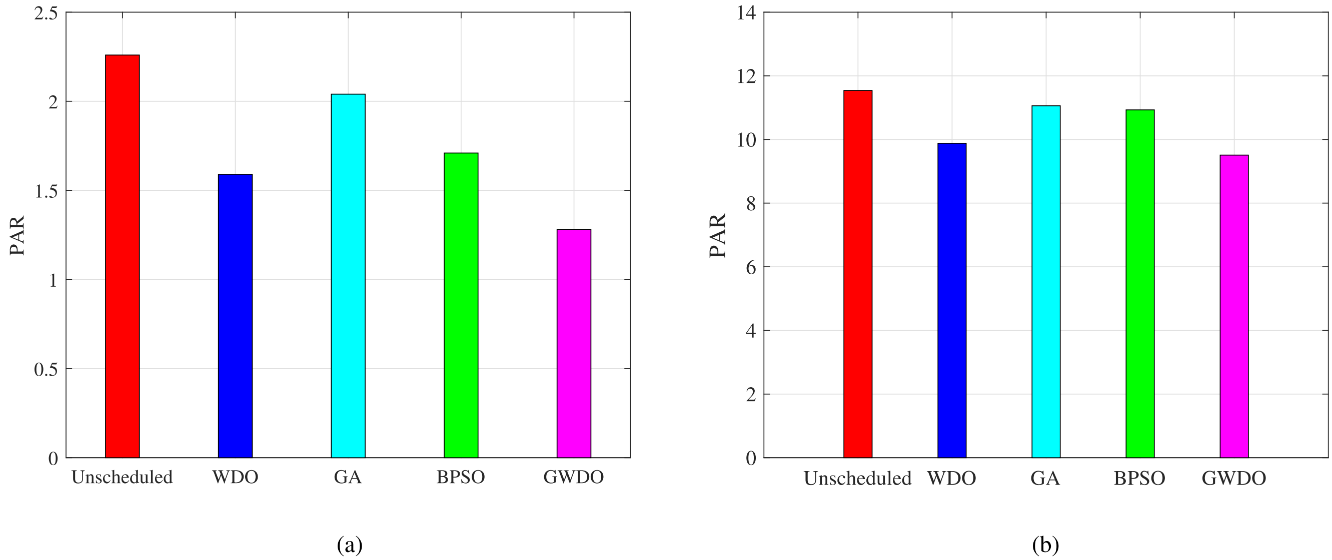

FIGURE 10. PAR analysis. (a) Single home. (b) Multiple homes.

RTP and IBR pricing scheme, power elasticity and shifting loads from the maximum peak to minimum peak price timeslots. Moreover, the values: 2.25, 2.09, 1.7, 1.55 and 1.35 are the unscheduled and scheduled loads of the PAR based on the GA, BPSO, WDO, GWDO, respectively. Additionally, it can be observed from the results that significant differences in unscheduled and scheduled loads using the GA, BPSO, WDO and GWDO is 7.11%, 24.4%, 31.1% and 40%, respectively. Figure 10a shows the PAR analysis for five homes per day. The load scheduled based on the GA, BPSO, WDO and GWDO in the presence of dynamic OTS and dynamic power ratings reduces the PAR as depicted in Figure 10b. Moreover, the percent decrement of the GWDO is more compared to other heuristic techniques as listed in Tables 8 and 7.

TABLE 7. Single home PAR analysis.

Techniques	PAR	Difference	Percent decrement (%)
Unscheduled	2.25	-	-
BPSO	1.7	0.55	24.4
WDO	1.55	0.7	31.1
GA	2.09	0.16	7.11
GWDO	1.35	0.8	40

F. AVERAGE WAITING TIME

Time elastic appliances have more average waiting time (i.e., 10 timeslots), because these appliances are delay tolerant and have time elastic nature. Unlike time elastic appliances, power elastic appliances tolerate the flexibility in power and have minimum waiting time. Essential appliances

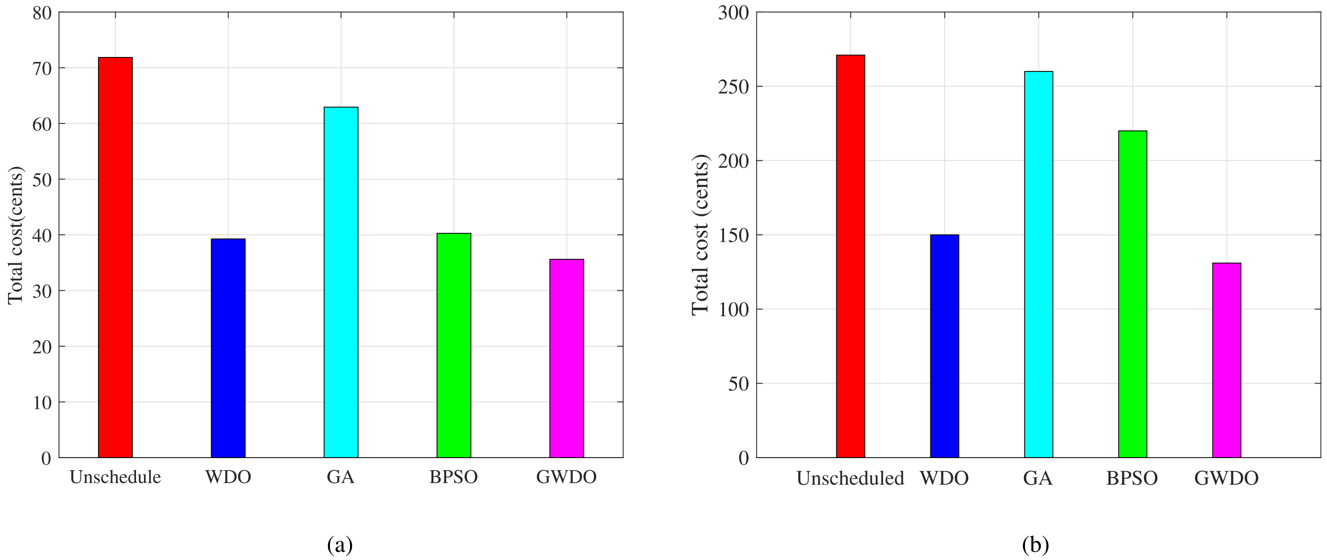

FIGURE 11. Aggregated cost analysis. (a) Single home. (b) Multiple homes.

TABLE 8. Multiple homes PAR analysis.

Techniques	PAR	Difference	Percent decrement (%)
Unscheduled	130	-	-
BPSO	90	40	30.7
WDO	85	45	34.6
GA	115	15	11.5
GWDO	81	49	37.69

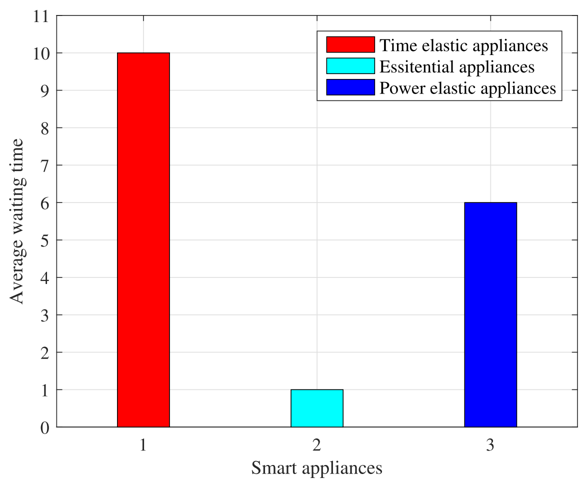

FIGURE 12. Average waiting time.

have less waiting time as compared to time elastic appliances and more waiting time as compared to power elastic appliances as shown in Figure 12.

G. AGGREGATED COST COMPARATIVE ANALYSIS

The comparison of unscheduled and scheduled loads with respect to electricity cost for a single home and multiple homes is depicted through Figure 11. Whereas, per day cost of the electricity for unscheduled and scheduled loads is 71,

TABLE 9. Single home total cost comparative analysis.

Techniques	Total cost (cents)	Difference	Percent decrement (%)
Unscheduled	71	-	-
BPSO	41	30	42.25
WDO	39	32	45.07
GA	64	7	9.85
GWDO	37	34	47.88

64, 41, 39 and 37 cents, against the GA, BPSO, WDO and GWDO, respectively, as illustrated in Figure 11a. Moreover, the highest cost is for unscheduled load which is 71 cents, because in the unscheduled case most of the appliances operate during on-peak intervals. All heuristic techniques follow the objective function and constraints that results in the reduction of electricity cost as compared to the unscheduled load as listed in Table 9. The cost reduction by the GWDO is more (47.8%) as compared to the unscheduled and scheduled loads by the GA, BPSO and WDO because it applies to the population based genetic operators on the optimal values of the WDO instead of random values. The per day cost of five homes is depicted in Figure 11b. The EMCU based on the GA, BPSO, WDO and GWDO schedules load using the objective function, constraints, control parameters, users dynamic OTS and power rating for electricity cost reduction. The results proved the efficiency of the system for scheduling by implementing the GWDO, GA, BPSO and WDO is 260, 220, 150 and 131 cents, respectively.

H. COST ANALYSIS WITH RESS AND WITHOUT RESS

In Figure 13, the relation between the electricity cost and users with the RESs is dipected. It is clear form the figure that an increased number of users with the RESs play a very important role in electricity cost reduction. As the GEC depends only on energy of electricity grid station, it pays more cost of 250 cents as compared to users with RESs.

TABLE 10. Multiple homes total cost comparative analysis.

Techniques	Total cost (cents)	Difference	Percent decrement (%)
Unscheduled	271	-	-
BPSO	220	51	15
WDO	150	121	44
GA	260	11	11
GWDO	131	140	48

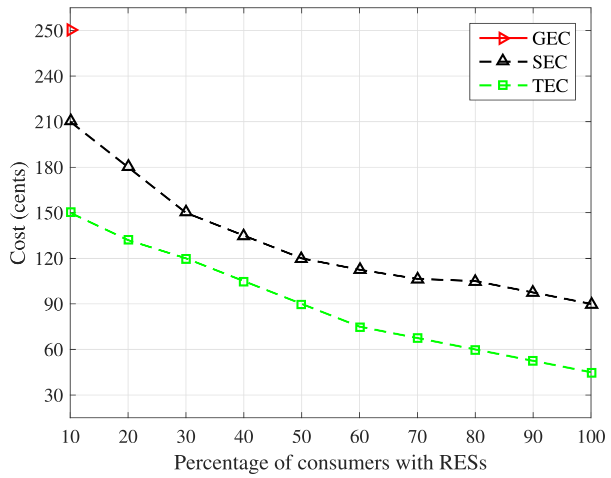

FIGURE 13. Cost versus percentage of users utilizing RESs.

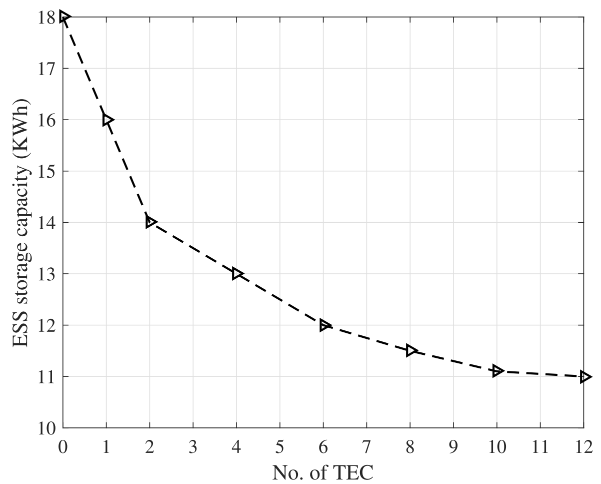

FIGURE 14. ESS storage capacity versus TEC.

The SEC fulfills its load demand from RESs, ESS and grid station. However, it does not take part in the local energy trading, so its electricity cost is 210 cents more then the TEC. The percentage decrement of TEC's cost as compared to GEC and SEC are 40% and 24%, respectively.

I. TRADE OFF ANALYSIS OF ESS AND TEC

For a given storage capacity of ESS, the cost of energy exchange decreases with the increase in the number of the TEC. This is because of a greater number of TEC available to generate and share energy among neighboring consumers and hence mitigate the need of borrowing energy from the electricity grid station as shown in Figure 13. It can be seen from Figure 14, that for a given number of TEC, there exist an optimal storage capacity of ESS. It is evident that as the number of TEC increases, the need of optimal storage capacity of ESS decreases because the TEC will provide energy to neighbors with low cost.

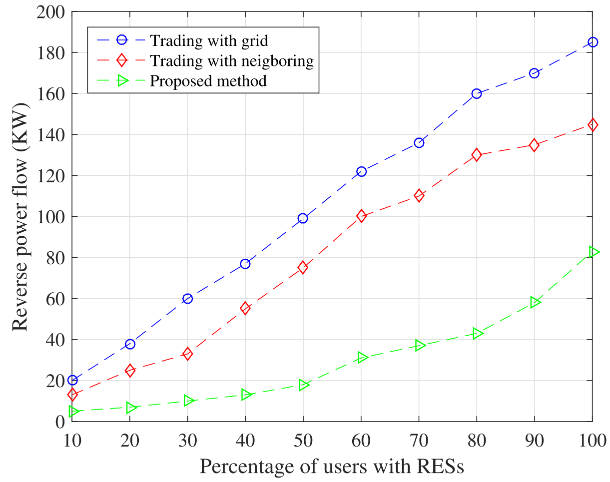

FIGURE 15. Reverse power flow versus percentage users with RESs.

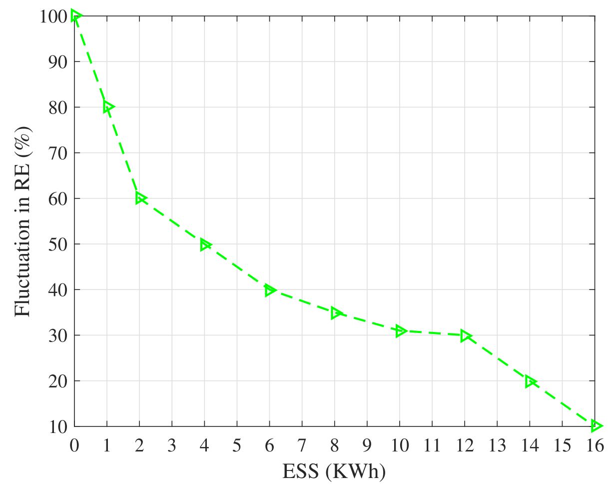

FIGURE 16. Fluctuations versus ESS.

J. REVERSE POWER ANALYSIS

The efficient utilization of RESs in consumers' premises encourages users to trade excess energy with neighboring consumers in order to reduce the reverse power flow. The trading energy with the utility grid injects reverse power flow which causes the voltage rise problem that may damage the entire power system. To evaluate the effect of our proposed method on the reverse power flow due to the gape between the supply and demand is illustrated in Figure 15. The reverse power flow is significantly reduced by our proposed method. The reverse power flow is maximum when the TEC trades energy with the grid and less when it trades with neighboring consumers. The simulation results validate that the proposed scheme significantly reduces the reverse power flow as compared to other scenarios.

K. FLUCTUATIONS WITH RESPECT TO ESS

We plot fluctuations of the RESs as a function of the ESS as illustrated in Figure 16. It ensures that as the capacity of the ESS increases the fluctuations of RESs decrease and hence results in smooth generation. It also ensures that the aggregate energy production of TEC meets the net load demand and smooth out fluctuations of RESs by storing, exchanging and trading the surplus energy. With no ESS, the RESs have 100 % fluctuations whereas, with the maximum capacity of the ESS and trading very low fluctuations that exist in the RESs.

VI. CONCLUSION

In this paper, we have proposed the heuristic based techniques for the DSM and energy efficient integration of RESs in the SG. An EMCU based on heuristic algorithms (GA, BPSO, WDO and GWDO) is used to schedule the household appliances in order to achieve our desired objectives. The RTP and IBR are combined to increase the stability of the proposed system. Additionally, the energy efficient integration of RESs is facilitated using the ESS and power trading among consumers. Simulation results show that our scheme is useful in terms of: the electricity cost, PAR and in minimizing the tradeoff between the electricity cost and the user comfort. Furthermore, our proposed scheduling solution for the DSM and energy efficient integration of RESs is useful for both, the utility company and the consumers. In addition, the proposed system model is suitable for designing the power grid by selecting the optimal combination of the ESS and the power trading, facilitating the energy efficient integration of RESs for reducing the electricity cost and the reversing power flow.

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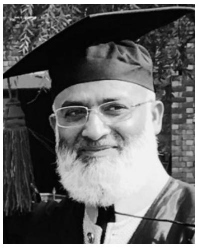

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