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Exploiting Nature-Inspired-Based Artificial Intelligence Techniques for Coordinated Day-Ahead Scheduling to Efficiently Manage Energy in Smart Grid

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ABSTRACT The increasing load demand in residential area and irregular electricity load profile encouraged us to propose an efficient Home Energy Management System (HEMS) for optimal scheduling of home appliances. We propose a multi-objective optimization based solution that shifts the electricity load from On-peak to Off-peak hours according to the defined objective load curve for electricity. It aims to manage the trade-off between conflicting objectives: electricity bill, waiting time of appliances and electricity load shifting according to the defined electricity load pattern. The defined electricity load pattern helps in balancing the load during On-peak and Off-peak hours. Moreover, for real-time rescheduling, concept of coordination among home appliances is presented. This helps the scheduler to optimally decide the ON/OFF status of appliances to reduce the waiting time of the appliance. Whereas, electricity consumers have stochastic nature, for which, nature-inspired optimization techniques provide optimal solution. For optimal scheduling, we proposed two optimization techniques: binary multi-objective bird swarm optimization and a hybrid of bird swarm and cuckoo search algorithms to obtain the Pareto front. Moreover, dynamic programming is used to enable coordination among the appliances so that real-time scheduling can be performed by the scheduler on user's demand. To validate the performance of the proposed nature-based optimization techniques, we compare the results of proposed schemes with existing techniques such as multi-objective binary particle swarm optimization and multi-objective cuckoo search algorithms. Simulation results validate the performance of proposed techniques in terms of electricity cost reduction, peak to average ratio and waiting time minimization. Also, test functions for convex, non-convex and discontinuous Pareto front are implemented to prove the efficacy of proposed techniques.

INDEX TERMS Coordination, dynamic programming, knapsack, multi-objective optimization, Pareto front, meta-heuristic, nature-inspired, bird swarm and cuckoo search algorithm, multi-objective bird swarm optimization, hybrid technique, demand side management, demand response, smart grid.

ABBREVATIONS

AMI	Advanced Metering Infrastructure
BSO	Bird Swarm Optimization
CPP	Critical Peak Price
CSO	Cuckoo Search Algorithm
DR	Demand Response
DSM	Demand Side Management
EA	Evolutionary Algorithm
HEMS	Home Energy Management System

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ICT	Information and Communication Technology
MBBSO	Multi-objective Binary BSO
MBCSO	Multi-objective Binary CSO
MBHBCO	Multi-objective Binary Hybrid BSO and CSO
MBPSO	Multi-objective Binary PSO
MOCSO	Multi-objective CSO
MOPSO	Multi-objective PSO
MOBSO	Multi-Objective BSO
MOHBCO	Multi-Objective Hybrid BSO and CSO
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PAR	Peak to Average Ratio
PSO	Particle Swarm Optimization
RTP	Real Time Price
ToU	Time of Use

ACRONYMS

App^{α}	Appliance user request to be switched ON
App^{α}_{c}	List of appliances user wants to reschedule
App^{d}	A particular appliance d where $d \in D$, D total appliances
$App^{d}_{D_h}$	Appliance d working demanded hour
$App^{d}_{P_{rate}}$	Appliance d power rating
$App^{d}_{S_h}$	Appliance d scheduled hour
D	Dimension of search space, i.e., total number of appliances
$App^{d}_{W_t}$	Waiting time of an appliance
$Aval^{int}_{time}$	Available time interval
C	Cognitive constant
CO_2	Carbon dioxide
Dis	Euclidean distance
ϵ	Smallest constant to avoid 0 in denominator
$E.C^{hour}$	Electric cost during an hour
$E.C^{total}$	Total electricity cost
$E.L$	Aggregated load of ON appliances
$E.L^{S^T}$	Per hour complete list of scheduled load
$E.L^{unsch}$	Unscheduled electricity load
$E.P$	Complete list of 24-hours electricity price
$E.P^{hour}$	Electric price during a particular hour
$\mathcal{F}$	Vector function
FL	Frequency by which scrounger follows the producer
FQ	Frequency of a bird flight behaviours
Fit_i	Fitness level of a particle according to equation 13
H^{off}_{p}	Off-peak hour
H^{on}_{p}	On-peak hour
M	Total number of iteration
$mean_j$	Average position of the whole swarm
N	Length of search space
O_{cost}	Objective function for electricity cost
O_{load}	Objective function for load
$O.L^{hour}_{curve}$	Objective load curve for particular hour
O^{int}_{time}	Operational time interval
O_{total}	List of the objectives
O_{wait}	Objective function for waiting time of appliances
P_r	Probability constant for bird swarm
p^{a}_{r}	Probability of cuckoo egg identification
$\mathcal{R}$	Repository
S	Social accelerated constants
$sumFit$	Sum of the fittest value of swarm
$\wp$	Status of an appliance
$\eth$	Step size $\eth = 0.1$
γ	Constant to create the objective load
$\hat{g}_j$	Swarm global best position
$\hat{p}_{i,j}$	Bird previous best position
$\mathcal{X}$	Search space
$x_{i,j}$	Position of a particle in search space
x	Decision vector
$\mathcal{Y}$	Objective vector

I. INTRODUCTION

The integration of Information and Communication Technology (ICT) with electricity infrastructure revolutionize the traditional grid into smart grid [1]. The emergence of smart grid allows the consumers to play a flexible role in the resource management, monitoring and controlling the operations of the smart grid infrastructure. Moreover, the exchange of data between the smart utility (service provider) and end user is achieved using Advanced Metering Infrastructure (AMI). This provides bi-directional communication paradigm and also enables the consumers to customize the execution of appliance operations based on the electricity prices in particular time. Moreover, this supports the end users to become active from passive consumers in the smart grid using AMI [1].

With the availability of smart infrastructure, the utility is capable to monitor and respond to the varying demands of the consumers. It helps the utility to generate electricity and adjusts the pricing tariffs accordingly. The variation in the pricing tariffs depends on the peak load because of high power demand in a particular time period [2]. Furthermore, demand management mechanisms are employed in smart grid to fulfill the demand of electricity using the available resources. Demand management mechanisms are categorized into two main groups: Demanad Side Management (DSM) and Demand Response (DR). In former, the reactive approach is adopted by the utility to maintain the balance between supply and demand. In latter, the consumer is encouraged to shift load from On-peak (high prices) hours to Off-peak (low prices) hours to avoid blackouts [2].

Irregular pattern of electricity demand is observed because of the extensive and irregular usage of electric appliances in a residential area. This leads to imbalance electricity load over specific time intervals (i.e., during the On-peak hours) and destabilizes the utility. To avoid load peaks, the utility defines the price tariffs under the DR program for On-peak and Off-peak hours. In order to minimize the peaks formation, the research community is devoted to manage the load demand through various mechanisms in Home Energy Management System (HEMS). A HEMS properly manages and controls the electricity load through scheduling electrical appliances. If the electrical appliances are not properly scheduled and load is not shifted from On-peak to Off-hours, the stability of the utility can be compromised [3].

In literature, numerous energy management systems have been proposed [4]–[13] to encourage the consumer to shift the load during the Off-peak hours to reduce the electricity cost. However, the consumer has to compromise comfort in order to reduce the electricity bill by ignoring the waiting time for the operation of an appliance. Thus, it shows that a home load management is a multi-objective problem with multiple trade-offs regarding various targeted objectives.

The utility and electricity consumer can communicate and coordinate through AMI to reduce the burden on the utility, which also helps the consumer in reducing the electricity bill. The coordination among the appliances can help in dynamic scheduling, which increases the consumer comfort and also reduces the waiting time (i.e., to start operation) of appliances [16]. During real-time scheduling, a consumer can modify the schedule of the appliances by generating an interrupt. In this regard, Erol-Kantarci and Mouftah [17] propose appliance coordination with feed in energy management scheme to enable the consumers to turn ON an appliance as per the requirements with complete freedom. However, when consumer turns ON an appliance, it coordinates with the energy management unit for getting an appropriate time-slot, which increases the delay and results in consumers' discomfort. Authors in [18] extend the work done in [17] by incorporating coordination among the appliances based on waiting time to reduce the cost and the PAR. In [17] and [18], the appliances after coordination can only be turned ON at convenient time-slot. The freedom of scheduling appliance irrespective of electricity price and load is not provided, thus, a dire need for an efficient HEMS emerges, which can deal with sudden changes in the load demand without sacrificing the user comfort.

A. MOTIVATION

DSM strategies are developed to overcome the energy scarcity issues, which are created due to increasing demands of power. In this respect, load management based on DR is one of the most popular DSM strategies which is used to shift the load from On-peak to Off-peak hours. However, this shifting results in peaks creation during the Off-peak hours [3] and also increases the waiting time of the appliances. Additionally, this depicts that the electricity cost, Peak to Average Ratio (PAR) and the waiting time are the conflicting parameters which belong to the category of multi-objective problems. Many systems like [3]–[13] have been developed to overcome these conflicting objectives. The authors in [3] have considered the electricity cost and the stability of the utility, which is determined through PAR. The trade-off between electricity bill and user comfort is minimized by [4]–[12]. The parameters to measure the user comfort level are varied based on waiting time, indoor and outdoor temperatures [4]–[11]. Articles [3] and [12] targeted the stability of the utility and consumer's electricity bill reduction, while ignoring the waiting time of an appliance. The user comfort along with minimum cost (electricity bill) is achieved by [4]–[11] at the cost of peaks formation during Off-peak hours. These sudden peaks during Off-peak hours (due to load shifting) increase the burden on the generation unit. Thus, an efficient system is required to optimize the conflicting objectives for the betterment of the utility and end consumers.

To find the optimal solutions for the aforementioned problems [4]–[13], deterministic (conventional) and non-deterministic (meta-heuristic) techniques have been proposed. The performance of an optimization technique depends on the nature of the problem, the deterministic schemes are the best problem solvers in deterministic environment. However, if the problem is stochastic in nature, then meta-heuristic techniques are the most feasible to find an optimal solution.

The increasing popularity of nature-inspired meta-heuristic algorithms in solving real-time problems attracted the research community from numerous domains like science and engineering, decision making in business, etc. The nature-inspired techniques are capable in minimizing the computational complexity based on four features: self-learning, self-optimization, self-processing and self-healing [19]. Moreover, the earlier said features are the basic building blocks of any nature-inspired algorithm which make it more effective and efficient. Additionally, these algorithms are easy to implement, flexible to deal with broad range of problems and have high degree of ergodicity [20]. Furthermore, these algorithms have the ability to escape from local optima by exploration and exploitation mechanism and also have the ability to search multi-modal landscape with adequate diversity. The deterministic techniques make the assumption(s) of certainty, proportionality, etc., for the problem being optimized; however, few or no assumption is taken into consideration for a meta-heuristic algorithm [21].

With the vast exploration of features of nature inspired techniques, still, no universal technique has been proposed for solving all optimization problems. Thus, there is an opportunity to solve complex optimization problems by improving the existing or proposing new meta-heuristic algorithms [22]. Moreover, the meta-heuristic algorithms are widely used for finding a sub-optimal solution instead of locating an optimal solution from the given search space. This is the reason, we propose new nature-inspired optimization techniques: (1) Multi-objective Binary Bird Swarm Optimization (MBBSO) algorithm, which is the multi-objective version of BSO, its four searching strategies makes it efficient and effective during exploitation and exploration of the search space [23], (2) Multi-objective Binary Hybrid of BSO and Cuckoo search Optimization (MBHBCO) algorithm, which is a hybrid technique because combining two or more meta-heuristic algorithms enhance the performance [24]. In the proposed hybrid algorithm, Cuckoo Search Optimization (CSO) follows the BSO, although, BSO is efficient and effective; however, its convergence speed is slow as compared to CSO. To improve its convergence speed, CSO is hybridized with BSO to help in quick exploration of the search space for increasing the convergence rate.

This paper is an extension of [25], where only CSO is used to handle multi-objective home energy management problems. Whereas, in this paper, we use Pareto front optimization to deal with the conflicting objectives: electricity cost, waiting time and PAR reduction with and without coordination. The only difference in the day-ahead scheduling with coordination and without coordination is the decision making step. During the day-ahead scheduling, the final solution from the Pareto front solution set is selected using the Roulette wheel selection method. For the coordination based day-ahead scheduling, a solution is chosen first by the Roulette wheel method, then a final solution is generated after coordination among the appliances. Additionally, the system flexibility is our target for real-time scheduling by enabling the consumer to coordinate with HEMS at any time during the working hours as explain in [26]. Further, a consumer can request to reschedule any of the appliance in any time-slot 't'. During the process of rescheduling, the appliances coordinate with each other to decide which appliance is more suitable according to its power rating and current electricity price. In day-ahead scheduling, Pareto front based feasible solution is obtained using meta-heuristic techniques: MBBSO and MBHBCO. In order to schedule the appliances in real-time, coordination is incorporated. Coordination in both day-ahead and real-time scheduling is incorporated through dynamic programming in proposed HEMS.

B. MAIN CONTRIBUTIONS

In this work, coordination based day-ahead and real-time schedulers are proposed. While, the sole focus of this work is to tackle following conflicting objectives:

1) distance minimization between objective load curve and scheduled electricity load profile which eventually helps to minimize PAR,
2) electricity cost reduction and
3) user comfort maximization (i.e, waiting time minimization).

While maintaining the distance between objective load curve and scheduled electricity load profile user electricity bill (cost) and waiting time can be increased. Moreover, there is always a trade-off between 'cost and waiting time', and 'cost and PAR'. To reduce the trade-off between conflicting parameters, day-ahead scheduling with and without coordination is proposed. Further, real-time scheduling is performed to deal with real time changes. In without coordination day-ahead scheduling, meta-heuristics techniques are implemented to minimize the load and electricity consumption cost based on the defined objective functions. For coordination in day-ahead and real-time scheduling, dynamic programming is used for enabling coordination among the appliances. Both scheduling mechanisms are validated against every performance parameter (that are targeted objectives of this research work) through extensive simulations. Further, the performance metrics show that our proposed hybrid scheme effectively maintains a minimum distance between the objective load curve and scheduled electric load profile with minimum cost and maximum user comfort.

The rest of the paper is organized as follows. Section II reflects the state of the art work of different HEMS. Based on the literature analysis, defined problem is mathematically formulated in Section III-A and the proposed techniques are explained in Section IV. Section III incorporates the system model of proposed scheme using bio-inspired meta-heuristic technique. Simulations results are demonstrated in Section V. Finally, conclusion of the research is discussed in Section VI.

II. RELATED WORK

Home load management under DR is a challenging task in the sense that DR allows the user to alter the electricity load pattern, and get some incentives in term of electricity cost reduction. This is practically possible through scheduling home electric appliances. However, during scheduling, if we only focus on electricity cost minimization then other factors are affected, i.e., user comfort and PAR. For such conflicting objectives, an efficient solution is required. In this respect, a lot of work has been done and implemented in the real environment.

The objectives of the authors in [3] are electricity cost minimization and the maximization of utility confidence. Authors in [4], consider the electricity cost, the operational delay minimization and highlights the issues related to the safe operation of an appliance, especially, if working time is set by the scheduler during the absence of consumer or when user is sleeping. The authors in [3], propose Evolutionary Algorithm (EA) and approximate EA by formulating problem as a constrained multi-objective optimization problem and later, these techniques are adapted by [4]. The simulation results of [3] show that the approximate EA is more efficient as compared to EA; however, waiting time of an appliance is totally ignored. On contrary, the conflict between the electricity cost and the waiting time of user is resolved by Muralitharan *et al.* [5]. As we know that whenever appliances are scheduled from On-peak to Off-peak hours. Due to load shifting, the load is increased in Off-peak hours. To tackle this situation, utility defines a threshold and bound the user to use the electricity within the specified limit. If user exceeds the load limit, then he has to pay extra charges [5]. To avoid this situation, authors in [5] propose an architecture which is based on multi-objective EA. This maintains the energy usage under the threshold limit by temporarily disconnecting the running appliance and resume its operation later in the day, which may creates peaks in the last hours.

In [6], issues related to the reduction of electricity consumption and the cost associated with it are addressed. Authors state that the understanding of human behaviour

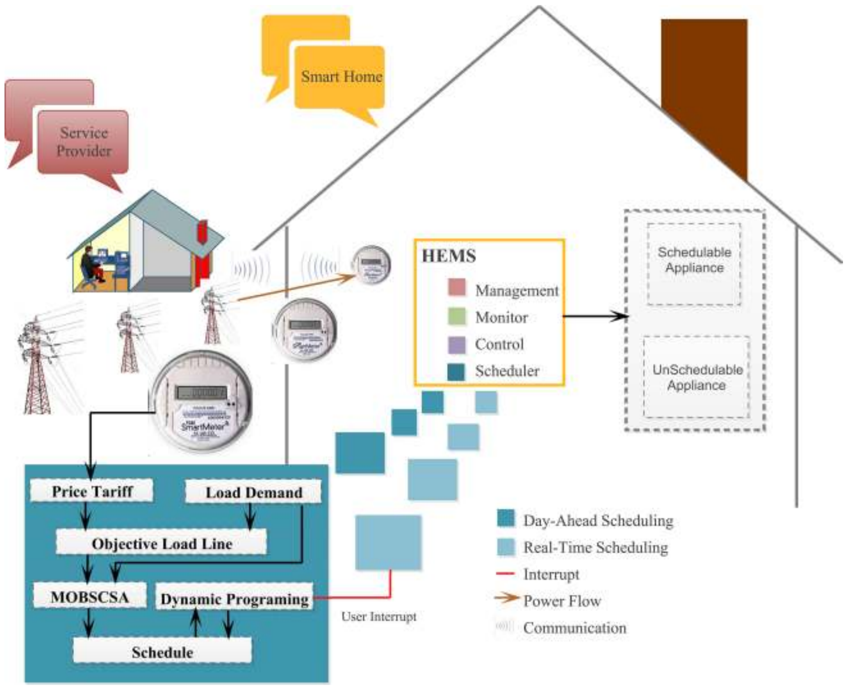


FIGURE 1. Systematic overview of HEMS and proposed model for scheduler of HEMS.

is very important for a successful system. In this perspective, the authors in [6] establish a human-behaviour-centric smart appliances rescheduling method. First, they predict the user behaviour and schedule the home appliances accordingly. Task management methodology and multi-objective based EA also known as Non-dominated Sorting Algorithm II (NSGA-II) are presented in [7], [8] and [9] to minimize the cost of electricity and consumers' dissatisfaction. In [9], authors study the user satisfaction level as level of inconvenience.

The aforementioned literature describes the user comfort in terms of waiting time of appliances; however, other factors also effect the user comfort level. The user comfort in terms of indoor and outdoor temperature is measured in [10]. Zhang *et al.* propose the modified Particle Swarm Optimization (PSO) algorithm for efficient scheduling of appliances while handling the trade-off among electricity bill and user comfort. They adapt the weighted sum method to solve the optimization problem. Similarly in [11], the system design is based on the Multi-Objective PSO (MOPSO) to solve the conflict between energy consumption and user comfort in a complex building. The trade-off between, overall production cost minimization, individual electricity bill reduction and user satisfaction maximization is handled by [12]. To achieve the aforementioned objectives mixed integer model is employed. Lokeshgupta *et al.* in [14] and Muhsen *et al.* in [15] employed mixed integer linear programming model and EA to minimize the user electricity bill and peak load demand, respectively. Authors in [13] tackle the three conflicting objectives: maximization of power demands, minimization of electricity cost and reduction in Carbon Dioxide (CO_2) emission using EA.

From literature analysis, it is observed that most of the researchers proposed the solution for two or more conflicting objective problems. Further, they ignored the user comfort while handling the electricity bill and utility stability. Though, some of the authors considered user comfort along with electricity cost; however, formation of peaks during the Off-peak hours is not considered.

III. SYSTEM MODEL

This section provides a systematic overview of the proposed scheduler of HEMS as given in Fig. 1 and overview of HEMS described in [27]. Our proposed model consists of smart devices, HEMS, smart meter and the service provider (utility). Whereas, HEMS manages the electricity load by monitoring, controlling and scheduling the controllable load [27]. The proposed system model contains two schedulers that perform day-ahead and real-time scheduling. The day-head scheduling is completed at the beginning of the day and it requires input parameters: electricity price and demanded load. Based on these input parameters, objective load curve is defined which helps in load scheduling. Moreover, user will be asked to list down priority appliances. Whereas, real-time scheduling will be performed during the day when a user generates an interrupt to switch OFF some appliance(s) and wants some priority appliances to be rescheduled in this available empty slot. The coordination will be performed here where scheduler will coordinate with appliances and appliances coordinate with each other.

As a result of this coordination, the empty slot will be allocated to the appliance(s) who will be fitted in that available slot. In real-time scheduling, the day-ahead schedule of home electric appliance(s) will be updated.

The proposed day-ahead load scheduling system is multi-objective, where each objective has equal importance. These objectives are: minimization of distance between objective and scheduled load pattern, electricity cost reduction, PAR and waiting time minimization. This strategy is helpful for both end user and the utility where day-ahead or seasonal prices are adapted. It benefits the user by reducing electricity bill and minimize the extra generation cost on the utility side by minimizing PAR. On contrary, real-time rescheduling is a single objective problem which aims to maximize user comfort in terms of accomplishment of user demand in real time. Real-time scheduling starts whenever user generates a run-time interrupt during the operational time of electric appliances.

A. MATHEMATICAL MODELING

Due to unscheduled load, the peak generations are inevitable and result in high electricity consumption cost, more discomfort of the consumer and degradation in the performance of the utility. In this section, we formulate a mathematical model to show the relationship of variables in achieving the desired objectives. Each objective function is separately defined along with its decision variables to control the system inputs for achieving desired outputs. In this section, the formulation of HEMS is performed for day ahead and real time scheduling for achieving the following objectives.

1) DAY-AHEAD HEMS

In order to schedule the appliances with day-ahead mechanism, load is shifted from On-peak to Off-peak hours. Moreover, the consumer can manage load according to objective load curve, minimization of electricity cost, and less appliance's waiting time. Further, the consumer can reduce the PAR with the help of DSM strategy load shifting. Some parameters are inversely proportional to each other like consumer comfort and electricity cost, and PAR and electricity cost, thus multi-objective optimization is also possible to handle trade-off. The formulation of each objective function along with its decision variables is given as follows:

a: LOAD MANAGEMENT

The load management is enabled in scheduler via shifting the load from on peak to off peak hours. The decision of load shifting is dependent on the objective load curve [28]. Whereas, the objective load curve is inversely proportional to the electricity market prices [28]. Our objective is to minimize the gap between the objective load curve and scheduled load curve. Additionally, the 24-hour time period is divided into On-peak and Off-peak hours according to the provided electricity rates. The mathematical expression of the objective function is computed as follows:

$$O_{load} = min(Dis|E.L^{hour}_{sch},\ O.L^{hour}_{curve}|), \tag{1}$$

constraints on the decision variables are defined as:

$$O.L^{hour}_{curve} = \begin{cases} \gamma \times mean(E.L^{unsch}) - std(E.L^{unsch}) & H^{off}_p, \\ std(E.L^{unsch}) & H^{on}_p. \end{cases} \tag{2}$$

The constant γ is adjusted based on the electricity demand or the unscheduled load $E.L^{unsch}$ by energy management controller. The constraint for $\gamma = 2$ and restriction on the objective load curve during On-peak hours H^{on}_p is that it's value should be less than Off-peak hour H^{off}_p. The constraints on both decision variables are given in the following mathematical expression.

$$\begin{aligned} &H^{on}_p \ if \ E.P^{hour} > mean(E.P^H), \\ &H^{off}_p \ if \ E.P^{hour} \leq mean(E.P^H). \end{aligned} \tag{3}$$

In equation 3, the decision is made about load shifting from H^{on}_p to H^{off}_p when the electricity price $E.P^{hour}$ in a particular hour is greater than the mean of electricity price $E.P^H$. The Off-peak hour is decided based on the $E.P^{hour}$ which must be equal to or less than the $E.P^H$.

As we discussed earlier, different parameters have inverse relationship and constraints on the decision variables are applied to handle the trade-off. Similarly, in this objective function, the objective load curve $O.L^{hour}_{curve}$ during particular hour is inversely proportional to electricity price $E.P^{hour}$, which is mathematically modeled as follows:

$$O.L^{hour}_{curve} \propto \frac{1}{E.P^{hour}}. \tag{4}$$

The aggregated electricity load $E.L$ of ON appliances during a particular hour is calculated using equation 5.

$$E.L = \sum_{d=1}^{D} App^{d}_{P_{rate}} \times \wp, \tag{5}$$

where $\wp$ represents the status of an appliance d, its value would either be 1 or 0. This variable shows whether an appliance is contributing in creating peak through 1 which is the ON status and 0 represents the OFF status of an appliance App^d during particular hour means an appliance is not involved in peak generation. Moreover, the power rating of controllable appliances is given in Table 2.

b: ELECTRICITY COST MINIMIZATION

In the discussion of load management, equation 4 describes the inverse relationship of load and electricity price. Moreover, through scheduling, load form On-peak hours will be shifted towards Off-peak hours because of high electricity demand during On-peak hours which is a major factor in high electricity prices. Therefore, our next objective is to minimize cost collectively for all ON appliances. The status of ON appliances is computed via equation 5. The objective function of cost minimization is mathematically written as:

$$O_{cost} = min(E.C^{total}). \tag{6}$$

The minimization of electricity consumption is directly proportional to the reduction in electricity cost, therefore, the decision variables of O_{load} defined in equation 2 are used for electricity cost minimization. The total electricity cost $E.C^{total}$ is calculated as:

$$E.C^{total} = \sum_{hour=1}^{H} (E.C^{hour}). \tag{7}$$

In order to calculate $E.C^{hour}$ of each hour for scheduling appliances, equation 8 is formulated.

$$E.C^{hour} = \sum_{d=1}^{D}(E.P^{hour} \times App^{d}_{P_{rate}} \times \wp). \tag{8}$$

c: APPLIANCES' OPERATIONAL WAITING TIME MINIMIZATION

In greedy approach of load and electricity minimization, the waiting time of appliances with high power rating increases with the increase in number of appliances. Therefore, it is worth mentioning, if an electricity consumer wants to reduce the electricity bill then he has to pay some cost in terms of waiting time which shows that electricity cost and waiting time are inversely proportional to each other. Thus, the next targeted objective is minimization of waiting time of an appliance $App^{d}_{W_t}$.

$$O_{wait} = min(App^{d}_{W_t}), \tag{9}$$

the waiting time of an appliance $App^{d}_{W_t}$ is calculated according to equation 10.

$$\begin{aligned} App^{d}_{W_t} &= |App^{d}_{D_h} - App^{d}_{S_h}|, \\ such\ that\ W_t &\leq 24\ hour. \end{aligned} \tag{10}$$

The waiting time of the appliance $App^{d}_{W_t}$ should be less than 24 hours. The constraint helps in ensuring that the desired appliance will be scheduled at least once within 24 hours time domain.

d: PAR MINIMIZATION

The objectives of load management, electricity cost minimization and reduction in operation waiting time of an appliance have direct influence on the consumer comfort. However, the stability of the grid can not be ignored because giving preferences to consumer could lead peak generations. Thus, we also target to reduce PAR because it directly effects the price specially Real Time Price (RTP) tariffs. The objective function for PAR minimization is written as follows:

$$O_{PAR} = min(PAR). \tag{11}$$

The objective defined in equation 11 is achieved through the management of load using equation 2. The PAR of objective function is calculated as given in equation 12.

$$PAR = \frac{max(E.L^{S^T})^2}{(avg(E.L^{S^T}))^2}, \tag{12}$$

where $S \in \{sch\ and\ unsch\}$, sch and $unsch$ represent scheduled and unscheduled electricity load, respectively. Whereas, $E.L^{S^T} = \{E.L^{S^1}, E.L^{S^2}, E.L^{S^2}, ..., E.L^{S^H}\}$ is a list of per hour electricity load calculated by equation 5.

e: MULTI-OBJECTIVE OPTIMIZATION

The earlier defined objectives: load management, electricity cost minimization, reduction in service operation waiting time and minimization of PAR are conflicting objectives and require a multi-objective optimization solution. These objectives are efficiently solvable by Pareto front: a set of solutions in search space $\mathcal{X}$ which are superior than other solutions for all objective vectors $\mathcal{Y}$ also known as Pareto optimal [29]. These solutions are non-dominated, for which $\mathcal{F}_i(x)$ cannot be improved in any dimension without degrading it in another dimension. Generally, a multi-objective optimization problem can be described as a vector function that maps decision vector $\mathbf{x}$ to objective vector $\mathcal{F}(x)$. Whereas, a possible solution is obtained while assigning values to the decision variable(s) [7], here decision variables are: On-peak hours and Off-peak hours, ON and OFF status of an appliances which directly influence the defined objective functions. At the end, a final solution is selected from non-dominated solution set by decision maker on the basis of some predefined criteria [30].

Formally:

$$\begin{aligned} &min(\mathcal{F}(x)), \\ &where\ \mathcal{F}(x) = (\mathcal{F}_1(x), \mathcal{F}_2(x), \cdots, \mathcal{F}_k(x)). \end{aligned} \tag{13}$$

In our scenario of day-ahead scheduling, $O_{total} = \mathcal{F}(x)$ and $O_{total} = (O_{load}, O_{cost}, O_{wait})$.

2) SINGLE-OBJECTIVE REAL-TIME HEMS WHILE INCORPORATING COORDINATION

In order to utilize the available resources like electricity optimally in real-time HEMS, the concept of coordination among the appliances is very vital to turn OFF or turn ON any of the appliance. This provides the flexibility in the use of system by allowing the consumers to interrupt any appliance (means only interruptible appliances not fixed appliances) and execute the operations of the desired appliance. With this interruption, the HEMS is capable to reschedule the appliance without degrading the performance of the system. This flexibility has been added because of the real-time coordination among the appliances using dynamic programming. The rescheduling of the appliances by the HEMS is known as real-time rescheduling and it helps in reducing the waiting time of particular rescheduled appliance. The system starts working whenever it receives an interrupt $\hat{I}$ from the user.

The mathematical representation of this run-time coordination is given as follows:

$$\wp = \begin{cases} 0, & \text{if } \hat{I} \text{ is generated,} \\ 1, & \text{otherwise.} \end{cases} \tag{14}$$

If the interrupt is generated by the consumer, the appliance is turned Off which is represented through $\wp$. In equation 14, the "0" denotes the Off state of the appliance due to the interrupt generation from the consumer and "1" means that the appliance is running and interrupt is generated for that particular appliance to terminate its operations.

$$App^{\alpha} = \begin{cases} 1, & \text{if } \hat{I} \text{ is generated,} \\ 0, & \text{otherwise.} \end{cases} \tag{15}$$

where $App^{\alpha} \in App_c^{\alpha}$, App^{α} is an appliance that is being switched ON in the result of interrupt generation. While App_c^{α} is the list of appliances that user wants to reschedule in real-time. To switch ON an appliance, the scheduler will check the compatibility of available time interval ($Aval_{time}^{int}$) with operational time interval (O_{time}^{int}) according to the following equation.

$$O_{time}^{int} \leq Aval_{time}^{int}. \tag{16}$$

User comfort and waiting time $App_{W_t}^{d}$ has an inverse relation, this relationship is mathematically expressed using equation 17.

$$Comfort \propto \frac{1}{App_{W_t}^{d}}. \tag{17}$$

In equation 17, *Comfort* is high, if the waiting of the appliance is less, however, this will increase the electricity consumption cost. As this is related to single objective optimization, thus, we are only concerned with the consumer comfort. Thus, the objective of maximum consumer comfort with the help of coordination through dynamic programming is achieved.

IV. PROPOSED METHODOLOGY

A vast range of optimization algorithms are available to solve the home appliances' scheduling problem. These algorithms could be deterministic or stochastic. The deterministic algorithm follow the same working procedure while the latter one has some randomness. The selection of these optimization techniques depends on the targeted objectives [31]. In this study, our proposed HEMS consists of two parts, one is for day-ahead scheduling which has multiple-objectives and second one is real-time rescheduling with only one objective. Former schedules the electric appliances for bill and PAR reduction. The later one is introduced to incorporate coordination among HEMS and electric appliances. The real-time scheduling problem is formulated as knapsack problem and dynamic programming is implemented to solve it. In this section, day-ahead and real-time rescheduling algorithms are elaborated sequentially.

A. MULTI-OBJECTIVE OPTIMIZATION FOR DAY-AHEAD SCHEDULING

In this underlying section, we elaborate the multi-objective day-ahead scheduling using proposed MBBSO and MBHBCO for HEMS.

The targeted objectives of day-ahead multi-objective optimization are: distance minimization between objective electricity load curve and scheduled load pattern, electricity cost, PAR and waiting time minimization. As discussed previously, trade-off exists between cost and PAR, cost and waiting time, and between the objective load curve and waiting time. Furthermore, analysis concludes that the electricity demand of user changes every day, so system must have the ability to deal with different pricing tariffs. This stochastic nature of user and price requires an efficient system to deal with multiple-objective problem.

Multi-objective optimization problems have conflicting objectives, as no single solution can be named as an optimum solution. To overcome conflicts (trade-offs), a feasible region is formulated through number of optimal solutions known as Pareto front. Mathematical and nature-inspired (bio-inspired) optimization techniques have been proposed to get Pareto front. Selection of these schemes depends on the nature of problem. Mathematical optimization techniques perform a series of steps to get Pareto front. On contrary, bio-inspired techniques set possible solutions in a single run. In this perspective, different statistical, mathematical and nature-inspired algorithms have been proposed and still researchers are looking for new techniques.

In this respect, we have proposed MBBSO (an extension of existing algorithm BSO) and MBHBCO (Hybrid version of MBBSO and MOCSO) algorithms to optimize the search space for load shifting under DR. Further, we evaluate the performance of proposed optimization algorithms by comparing the simulation results with existing MBPSO [32] and Multi-objective Binary CSO (MBCSO) [33]. BSO and MBCSO are selected because of simulations conducted in [24] and [33] validate the stability, effectiveness and superiority of BSO over PSO and DE, and that of MBCSO over NSGA-II and MODE. In the next section, we give a brief introduction of proposed MBBSO, MBHBCO and existing MBCSO.

1) MBBSO

BSO is a swarm based algorithm, it was introduced in [24]. The swarm intelligence behaviour of birds is adapted to solve the optimization problems. MBBSO algorithm has the merits of both PSO and DE which makes it extensible. We used BSO because it is more efficient, accurate and robust than PSO [24]. Moreover, it explores as well as exploits the search space with four different strategies and its convergence speed is also faster than PSO and DE. Further, MBBSO is inspired from bird swarms' social behavior and their interaction for foraging, vigilance and flight as presented in [24]. This social interaction helps the birds to forage food and escape from the predators.

BSO is an efficient algorithm for solving a single objective problem; however, its multi-objective optimization algorithm is not proposed. Thus, we have proposed MBBSO to solve multi-objective problems. The swarm is modeled as a search space to select an optimal solution and the position of each bird is decided based on the ON or OFF status of an appliance. The control parameters of algorithm are passed as input variables and random population is initialized and evaluated on the basis of defined objective function. These objectives are used for the fitness evaluation of the population and all non-dominated (Pareto front) solution sets υ are stored in archive $\mathcal{R}$. In each generation of MBBSO, first a leader is selected using Roulette wheel selection method that is $\hat{g}$ of swarm. Then birds will be divided into three groups and their positions will be updated accordingly, after that, $\mathcal{R}$ will be updated. After maximum iterations, using threshold limit, values are converted into binary form and an optimal solution as a schedule of specific hour is selected.

In our proposed system, the swarm is a search space $\mathcal{X}$ and its size is $N \times D$. The position of birds is decided through the ON or OFF status of an appliance. The probability of a bird to get the ON status of an appliance is P_r. The behaviour of BSO is idealized on the basis of five rules which are as follows [24]:

Rule 1: A bird decides his obligation (i.e., forages or keeps vigilance) and this decision is modeled as stochastic. Each bird is given the opportunity to switch between vigilance and foraging behaviour.

Rule 2: Social information is instantaneously shared with the whole swarm. During foraging, each bird can promptly record and update the previous best experience of its own swarm regarding food terminus which can help in food searching.

Rule 3: Birds with high reserves would have high probability to be closer to the centre of the swarm. During vigilance, each bird desires to move toward the centre.

Rule 4: Birds would fly periodically during this periodic flight where they often switch between scrounging and producing behaviours. Birds with highest and lowest reserves would be categorized as a producer and a scrounger, respectively.

Rule 5: A producer would be followed by scroungers randomly because producers actively hunt for food.

The basics of BSO are assimilated in proposed MBBSO for home load management. The working of the proposed algorithm is depicted in Algorithm 1. All N virtual birds are represented by their position $x^t_{i,j}$, for $i = 1, 2, 3, \ldots, N$ at time 't', forage for food, vigilance and flight in D-dimensional search space, for $j = 1, 2, 3, \ldots, D$. $randn(0, 1)$ depicts the random Gaussian distribution number with mean 0 and standard deviation 1. Each bird flies with the frequency FQ ($FQ > 0$) in a unit interval from one place to other.

For simplicity, the Rule 1 is formulated as a stochastic decision. If a uniform random number is between $[0 - 1]$ which is smaller than P_r ($P_r \in [0 - 1]$), a probability constant value then the bird would forage, otherwise continue vigilance. Each bird forage for food according to bird's own and swarm's experience [24]. In Algorithm 1, the control parameters of an algorithm are taken as input variables. The input varibales are: total number of time-slots (H), i.e., 24 in this scenario, number of appliances (D), total iterations (M) and tunning parameters (P_r, FQ, $a1$, $a2$, $S\ C$). Then random population is initialized and evaluated on the basis of defined objectives. These objectives are used for the fitness evaluation of the population. Then non-dominated solution set based on Pareto front is stored in $\mathcal{R}$. The next step is leader selection, i.e., $\hat{g}$ of swarm. Then the search space is updated using basic BSO steps. At the end, the search space is converted into binary form using threshold limit and an optimal solution is selected as a schedule of specific hour. Here, search space is considered as the set of possible solution sets, each swarm is taken as the possible combination of the appliances and each bird in the swarm is taken as an appliance.

2) MBCSO

Yang *et al.* proposed the MOCSO in article [33]. The working layout of CSO proposed by [35] is based on obligate brood parasitic behaviour of cuckoo bird combined with Levy Flight behaviour of some fruit flies. The basic structure of CSO can be simplified by given Rules [35]:

Rule 1: Each cuckoo lays only one egg at a time in a randomly chosen host nest.

Rule 2: The nests with high quality of eggs would be considered as best nests and will be proceed to the next generation.

Rule 3: Available host nests are fixed, if host bird identifies the cuckoo egg with a probability $p^a_r \in [0, 1]$ then the host bird either throws the egg or abandons old one and builds a new nest. For further simplicity, the abandon nests are replaced with new random nests.

For all N host nests, the new position for *ith* cuckoo for D-dimension (eggs) is performed by Lévy flight [35]. In this work, Lévy flight have random walk by Mantegna's algorithms is used because it is more efficient in search space exploration [35].

According to CSO algorithm, the number of host nests and the eggs of cuckoo will be the same, as one cuckoo can lay only one egg at a time. The above-mentioned steps of CSO are incorporated in MOCSO [33]. We have proposed its binary version MBCSO for HEMS scheduler as elaborated in Algorithm 2. In this algorithm, after the initialization of control parameters and population, the search space $\mathcal{X}$ is evaluated. Within maximum iteration (M), CSO steps are performed and the best nest is selected as a schedule for the current hour. The nest is selected from the non-dominated Pareto front set using the Roulette wheel selection method. Whereas, each egg represents the ON or OFF status of an appliance. If cuckoo' s egg is not recognized by the host bird, the appliance status updated as switched ON; otherwise, it is

Algorithm 1 Algorithm of Day-Ahead HEMS Scheduler Using MBBSO

Require: Input: $[H, D, N, M, P_r, FQ, FL, a1, a2, S, C]$
Initialization: Objective functions given in section III-A
$t = 0$, Random population ($\mathcal{X}$) of $N \times D$ and convert it into binary form BX
Evaluate the BX using equation 13,
Find the non-dominated solution sets and store in repository $\mathcal{R}$.
for $h \leftarrow 1$ to H **do**
  Start of MBBSO
  while $t < M$ **do**
    Select the leader ($\hat{g}$) form $\mathcal{R}$ using Roulette Wheel Selection.
    if mod $(t, FQ) \neq 0$ **then**
      for $i \leftarrow 1$ to N **do**
        if $rand(0, 1) < p_r$ **then**
          Update position of each bird form $\mathcal{R}$ Forage for food (Equation 1 given in [24])
        else
          Update position of birds keep vigilance form $\mathcal{R}$ (Equation 2 given in [24])
        end if
      end for
    else
      Divide the swarm in two groups: producer and scrounger
      for $i \leftarrow 1$ to N **do**
        if $i == producer$ **then**
          Update position of producer form $\mathcal{R}$ using Equation 5 given in [24]
        else
          Update position of scrounger form $\mathcal{R}$ using Equation 6 given in [24]
        end if
      end for
    end if
    Convert it in binary form Evaluate the fitness of updated BX (Equation 13)
    If the new updated solution dominated the previous one,
    Replace previous with current solution.
    Find the non-dominated solution set and update $\mathcal{R}$
  end while
  Select the leader $\hat{g}$ from $\mathcal{R}$
  End of MBBSO
  $Sch(h, D) = \hat{g}$
end for

switched OFF. Here, each cuckoo is an appliance and nest represents the possible ON or OFF states of the appliances. While updating the position, eggs within the nest appliances with more importance according to the current situation are converged towards the optimal point.

3) MBHBCO

In this section, we elaborate the proposed multi-objective hybrid bird swarm and cuckoo search optimization algorithm technique for Pareto front optimization. Generally, two or more optimization techniques are hybridized to get an efficient and effective scheme. Authors in article [23] stated that hybridization is performed to enhance the performance of an algorithm by embedding the best features of one algorithm into another algorithm. A hybrid model has two main aspects, the first refers to the method of hybridization whereas the second is the level of hybridization are explained as [23]:

Method of hybridization: a). meta-heuristic is combined with meta-heuristic, b). meta-heuristic is combined with other techniques.

Level of Hybridization: Defines the degree of coupling, control strategy and execution sequence elaborated as:

- *Degree of Coupling:* It is demarcated as loose coupled and strong coupled. The former is known as a high level of hybridization, where each technique maintains its identity, i.e., flow of each technique is fully followed, while the latter, is known as low level coupling, these techniques interchange their internal working procedure.
- *Control Strategy:* It is defined as coercive or cooperative. During coercive, one of the hybrid technique follows

Algorithm 2 Algorithm of Day-Ahead HEMS Scheduler Using MBCSO

Require: Input: $[H, D, N, M, P_r^a, \eth, \Upsilon]$

Initialization: Objective functions given in section III-A
$t = 0$, Random population ($\mathcal{X}$) of $N \times D$ and Convert it into binary form BX
Evaluate the BX and store in F using equation 13,
Find the non-dominated solution sets and store in repository $\mathcal{R}$.
for $h \leftarrow 1$ to H **do**
  Start of MBCSO
  while $t < M$ **do**
    Select the leader ($\hat{g}$) form $\mathcal{R}$ using Roulette wheel selection.
    for $i \leftarrow 1$ to N **do**
      Get each cuckoo position (x_i) and update $\mathcal{R}$
      Convert it in binary and updated $\mathcal{R}_{new}$
      Evaluate the fitness F_{new} (Equation 13)
      if dominate(F^i_{new}, F^i) **then**
        $x_i = x_i^{new}$ using Equation 1 given in [35]
      end if
    end for
    for $i \leftarrow 1$ to N **do**
      if $rand > p_r^a$ **then**
        $x_i^{new} = random\ walk$
        random walk using the Lévy flight
        Convert it in binary and updated BX_{new},
        Evaluate the fitness F_{new} (Equation 13)
        if dominate(F^i_{new}, F^i) **then**
          $x_i = x_i^{new}$ using Equation 1 given in [35]
        end if
      end if
    end for
    Find the non-dominated solution set and update $\mathcal{R}$
  end while
  Select the leader $\hat{g}$ from $\mathcal{R}$
  End of MBCSO
  $Sch(h, D) = \hat{g}$
end for

the flow of the other technique. Within the cooperative strategy, hybridized techniques cooperatively explore the solution space.

- *Execution Sequence:* It could be sequential or parallel.

From literature, it is analyzed that the optimal solution can be maximal or minimal. The minimal optimization problem can lead all the values toward zero, if the solution space requires maximum iterations. Whereas, maximal optimization can lead optimal point values toward the maximal point. To avoid such situation, an optimal solution is required that can keep values between minimal and maximal optimization. In this perspective, we hybridize two meta-heuristic techniques MBBSO (search for minimal optimization) and MBCSO (search for maximal optimization) through loosely coupled strategy. This strategy follows the sequential execution with coercive control strategy, where CSO steps follow the BSO steps.

The proposed hybrid scheme is based on the non-dominated Pareto front solution set. The complete work flow of MBHBSO is given in Algorithm 3. In this algorithm, during each iteration, best birds are passed as an input for the CSO and the non-dominated solutions are stored after converting them into binary form in an archive. These solutions are represented as non-dominated Pareto front. During the decision-making step, decision maker will select the global best as the final solution. In the considered HEMS scenario, host nests reflect the search space and eggs laid by cuckoo are taken as the ON/OFF status of electric appliances, if the egg is recognized by host bird, then the status of appliance will be OFF, otherwise, it will be ON.

4) PARETO FRONT OPTIMAL

The repository $\mathcal{R}$ is updated using Pareto front optimal solution set υ. The non-dominated υ_i is selected if $\upsilon_i < \nu_i$. Whereas, $i = \{1, 2, 3, \ldots, N\}$ and $\upsilon, \nu \in \mathcal{X}$.

5) DECISION MAKING

The last and important step for multi-objective problem is decision making in which decision maker has to select one

Algorithm 3 Algorithm of Day-Ahead HEMS Scheduler Using MBHBCO

Require: Input: $[H, D, N, M, P_r^R, \alpha, \Upsilon]$

Initialization: Objective functions given in section III-A
$t = 0$, Random population ($\mathcal{X}$) of $N \times D$ and Convert it into binary form BX
Evaluate the BX and store in F using equation 13,
Find the non-dominated solution sets and store in repository $\mathcal{R}$.
for $h \leftarrow 1$ to H **do**
  Start of MBBCO
  while $t < M$ **do**
    Select the leader ($\hat{g}$) form $\mathcal{R}$ using Roulette wheel selection.
    Algorithm 1 (Line 10-27) to update the population
    Updated population is passed as a initial population to Algorithm 2
    Algorithm 2 (Line 10-27) to update population
    Find the non-dominated set and update $\mathcal{R}$
  end while
  End of MHBBCO
  Select the leader $\hat{g}$ from $\mathcal{R}$
  $Sch(h, D) = \hat{g}$
end for

TABLE 1. Parameters of MBHBCO.

Algorithm	System Parameter	Value
MOBCSO	$\eth$	0.1
	P_r	0.1
	p_r^a	0.4
MOBBSO	$a1$	1
	$a2$	1
	C	1.5
	S	1
	FQ	10
MOBBSO	M	100
	N	200

of the optimal solutions from non-dominated solution set. Where an optimal point selection is quite challenging. During the study it is observed that load management is the key factor to minimize the electricity cost and PAR. During the decision making step dynamic programing based coordination among appliances is incorporated for efficient load management and compared with without coordination selection.

a Decision making without coordination
In day-ahead scheduling without coordination only roulette wheel, a probability based selection method is adapted for decision making.

b Decision making with coordination
In the decision making step of with coordination, first a solution is selected using roulette wheel selection method. After selection, some of the appliances can be switched OFF or ON through coordination. Appliance(s) is switched OFF, if the selected solution from the Pareto front shows more electricity load as compared to the $O.L_{curve}^{hour}$. However, if electricity load found less as compared to the $O.L_{curve}^{hour}$ some of the appliance(s) can be switched ON.

B. COORDINATION FOR DAY-AHEAD AND REAL-TIME SCHEDULING

Coordination for two different scenarios: day-ahead and real-time scheduling is presented in this paper. For day-ahead scheduling before finalizing the schedule coordination among the appliances is incorporated, so that electricity load can be closed towards the defined objective lines.

During the working hours, appliances are rescheduled in real-time on user request, while maintaining the effects of Off-peak and On-peak hours on electricity cost. Correspondingly, we follow a different approach in which appliance can be turned OFF through coordination during the given time interval and an empty slot will be allocated to another appliance after performing coordination between appliances as shown in Fig. 2.

If the user generates an interrupt, it results in triggering algorithm 4 as given in [26]. This algorithm describes scheduler and user coordination which is deployed using dynamic programing. For instance, a user intends to reschedule App_c^{α} and scheduler keeps these appliances on high priority. Through dynamic programing, it decides which appliance to turn ON. This decision is based on On-peak, Off-peak hours and available time interval.

To efficiently solve the day-ahead and rescheduling problem, it is formulated as knapsack problem. Real-time scheduling is a single-objective problem, where target is user comfort maximization by effective utilization of available time interval. This available time interval is considered as knapsack capacity and appliances are considered as the items to be filled in the knapsack. In this scenario, working time interval of an appliance is considered as a weight of an item. The cost of the operational time of an appliance is described as value of an item which depends upon the price rate of a particular hour and the power rating of appliances to be turned ON. At the end, we get an optimal solution by combining items with minimum weight and maximum value for an On-peak hour and maximum weight and minimum values for particular Off-peak hour. This optimal value should not exceed the knapsack capacity as explained in equation 16.

In case of day-ahead coordination, target is the load management, whereas according to the situation, an item is added or taken out from the knapsack. If the scheduled load exceeds the given objective load curve, some of the appliances are switched OFF; otherwise, knapsack is filled according to the available capacity through coordination. The dynamic programming is very effective in solving a knapsack problem when a single solution is required. Bellman in [36] introduced dynamic programming to solve the knapsack problem. It divides a problem into sub-problems and each sub-problem is solved separately using Bellman equation 18. Solution of each problem is kept in a table,

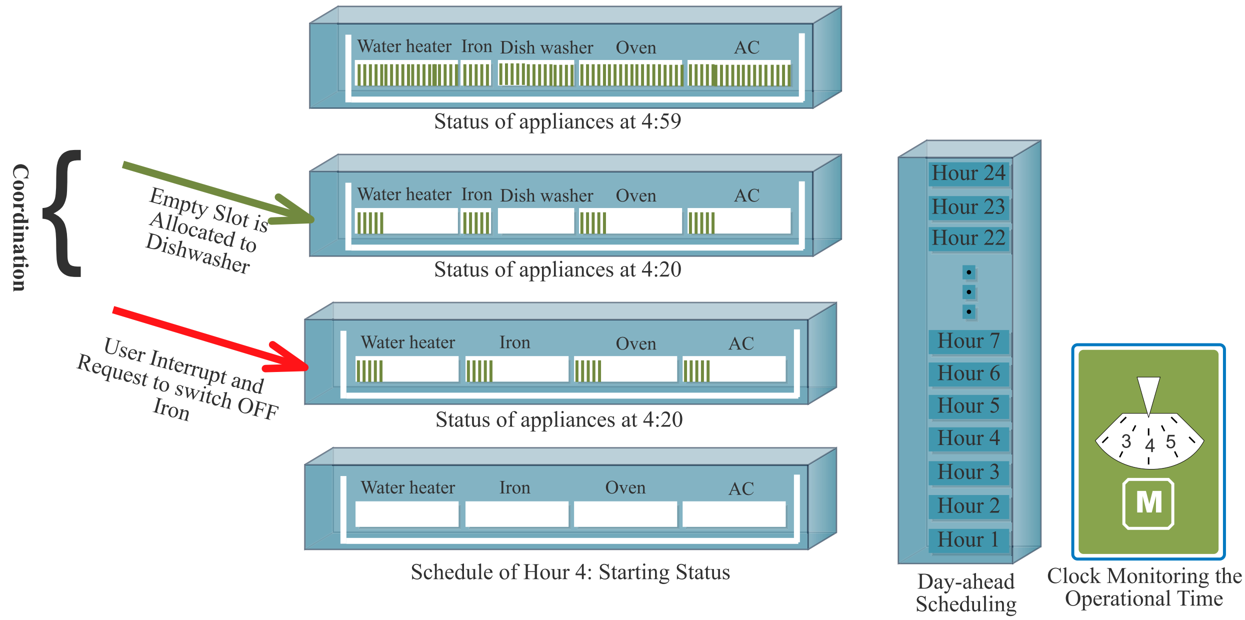


FIGURE 2. **Real-time scheduling through coordination: An example scenario.**

so that available solution can be used for the similar problem in future. We compute the results using the equation 19 and a table $T[\acute{i},\acute{j}]$ which is used to maintain these values. The possible solution which covers the maximum capacity and maximum benefit is stored in table $S[\acute{i},\acute{j}]$. The optimal solution from stored table is selected using equation 20. Based on this equation, the empty slot will be allocated to the priority appliance(s) or selected appliance(s) will be removed from schedle.

$$KS^{1,2}_{D_e} = [T[\acute{i}-1,\acute{j}], Value(\acute{i}-1) + T[\acute{i}-1, \acute{i}\acute{j} - List_{time}(\acute{i}-1)]]. \tag{18}$$

$$T[\acute{i},\acute{j}] = \begin{cases} max(KS_{D_e}), & \text{if } H_p^{off} \\ minKS_{D_e}, & \text{if } H_p^{on} \end{cases} \tag{19}$$

$$S[\acute{i},\acute{j}] = \begin{cases} 1, & \text{if } T[\acute{i},\acute{j}] == KS^2_{D_e} \\ 0, & \text{Otherwise} \end{cases} \tag{20}$$

V. SIMULATION RESULTS AND DISCUSSION

In this section, we discuss the simulations results to evaluate the effectiveness of the proposed multi-objective optimization techniques and system model. Effectiveness of proposed algorithms is proved by testing the techniques on defined bench-mark functions as given in Figs. 3-6.

The simulation results under discussion are the average of 5 Iterations. We also study the effect of coordination on electricity cost, PAR and waiting time. Furthermore, we present a comparative analysis of the proposed and existing multi-objective algorithms. We also study how different input parameters effect the performance of an algorithm. For this purpose, we carry out experiments for three different pricing schemes: RTP [28], Time of Use (ToU) [38] and Critical Peak Price (CPP) [38]. These pricing tariffs are shown in Figs. 8 (a)-(c), respectively. All simulations are carried out in MATLAB 2018a. The simulations results depict the energy consumption pattern and its effect on electricity cost, user comfort and PAR. The smart home consists of $D = 15$ appliances as shown in Table 2 along with their power ratings and daily usage. The power rating and daily usage of selected appliances are taken from [39] and [40].

These appliances are selected because of their extensive usage in all the seasons. The selected appliances are categorized into two groups: schedulable and non-schedulable appliances. Schedulable appliances are further classified as: interruptible and non-interruptible. Interruptible appliances can be scheduled on different time-slots, whereas non-interruptible appliances cannot be interrupted during the operational cycle. For example, washing machine cannot be interrupted once it starts its working, it will be turned OFF only after completion of its task. For day-ahead scheduling Interruptible appliances can be switcheeed Moreover, for the real-time scheduling, we consider the dish washer and vacuum cleaner as priority appliances in this scenario for simulation. As discussed previously, we consider the time-slot of one hour and each appliance is turned ON during its allocated time-slots. However, the working time of dish washer and vacuum cleaner could be less than an hour which depends on users' requirement.

A. MULTI-OBJECTIVE TEST FUNCTIONS

There are variety of test functions for multi-objective optimization techniques; however, a few of widely used functions provide a wide range of diverse properties in term of Pareto front. Through these test functions, a new proposed technique's effectiveness can be validated.

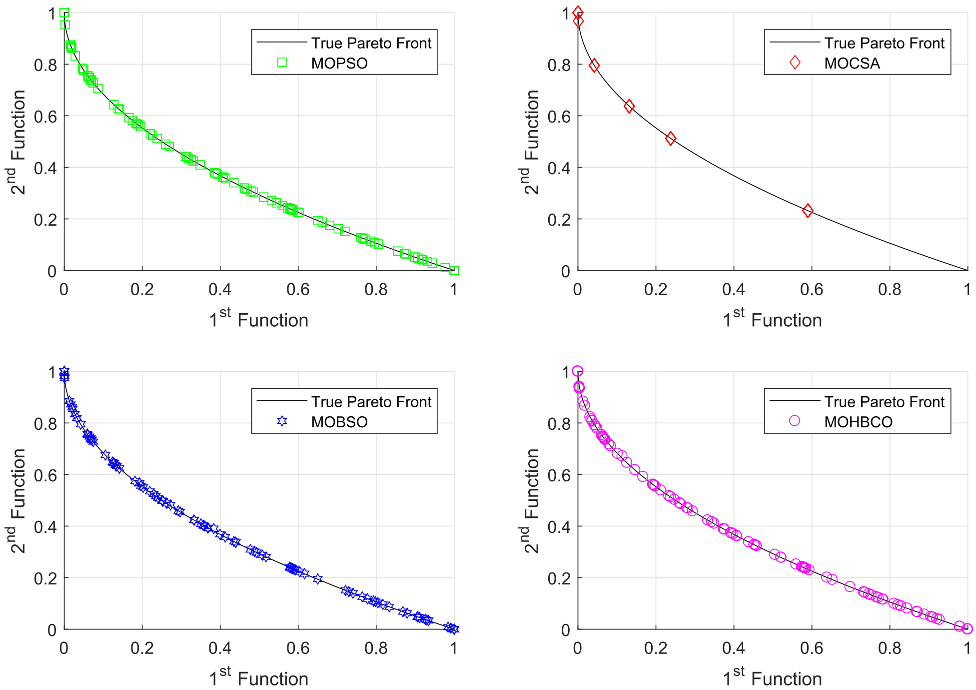


FIGURE 3. Graphical results of ZDT1 function of MOPSO, MOCSO, and proposed MOBSO and MOHBSCA.

TABLE 2. Appliances used in simulations.

Group	Appliances	Power Rate (kWh)	Daily Usage (hour)
Interruptible load	Vacuum cleaner	0.7	<= 3
	Water heater	5	8
	Water pump	1	8
	Dish washer	1.8	<= 3
	Iron	1	3
	Refrigerator	0.225	20
	AC	1.5	14
Non-interruptible load	Washing machine	0.7	5
	Cloth dryer	5	4
non-schedulable load	Oven	2.15	4
	Blender	0.3	1.5
	Light1	0.03	12
	Light2	0.03	10
	Light3	0.011	9
	Light4	0.18	8

In this study, to validate the MOBSO and MOHBCO, we have selected ZDT1 with convex Pareto front, ZDT2 with non-convex Pareto front, ZDT3 a function with discontinuous front values and ZTD4.

The graphical results in Figs. 3-6 show Pareto fronts obtained by the MOBSO and MOHBCO, which are compared with existing MOPSO and MOCSO algorithms. The curve lines in these figures get through meta-heuristic techniques (i.e., MOPSO, MOCSA, MOBSO and MOHBCO) are compared with the true Pareto front. The true Pareto front is taken form [37] During the experimental results, a premature convergence rate is being observed in case of MOPSO, which shows that MOPSO is trapped in local optima. Whereas, MOCSO techniques non-dominated solutions sets converge on very few points as can be envisioned in Fig. 3-Fig. 6. The Fig. 6 illustrates that the convex Pareto front with function ZDT4 for MOPSO is away form the true Pareto front where as proposed techniques front line is very close to the true line. Further, Mean Square Error (MSE) values for all four studied test functions are also calculated and given in Table 3. These results depict that MOPSO outperforms for the ZDT1 convex Pareto front whereas, it performs worse for ZDT4. For discontinuous Pareto set ZDT3, MOBSO shows high performances comparatively. Furthermore, study proves that with increasing number of dimensions of search space performance of existing techniques MOPSO and MOCSO degrades as shown in Table 3.

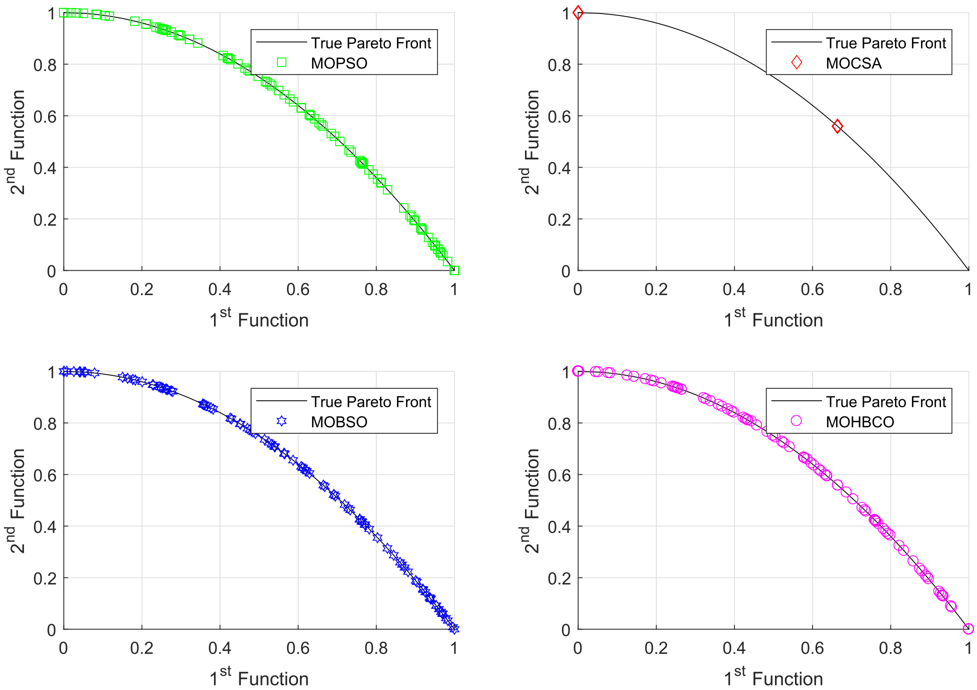


FIGURE 4. Results for the ZDT2 for all four optimization techniques.

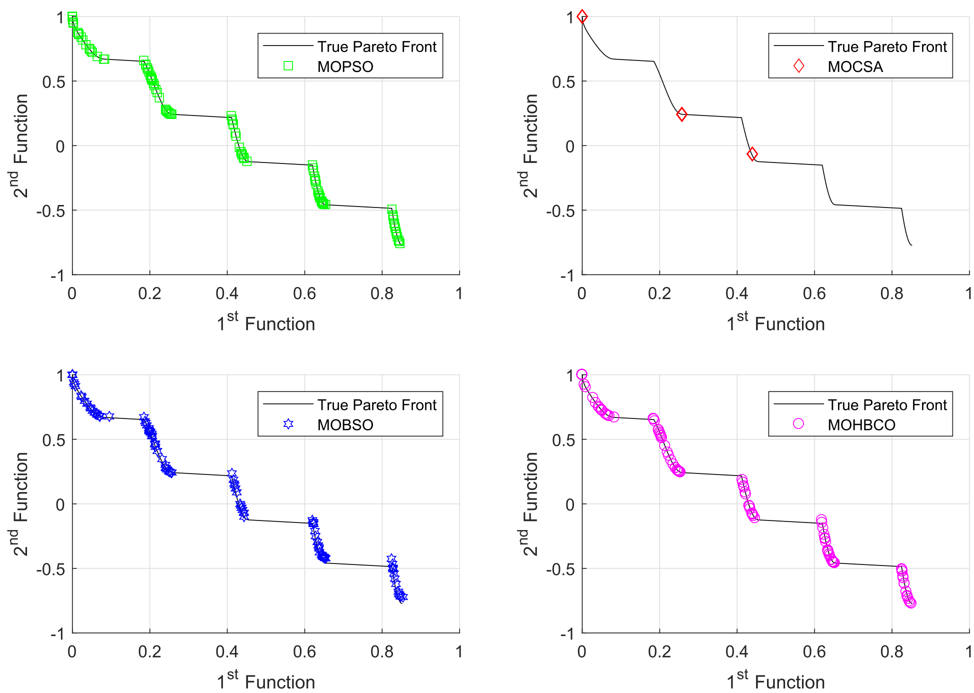


FIGURE 5. ZDT3 bench-mark test results for proposed MOBCA and MOHBSCSO, and existing techniques MOPSO and MOCSO.

B. DAY-AHEAD SCHEDULING WITHOUT COORDINATION

Here, we discuss the results of simulations conducted for day-ahead scheduling. Our aim is to minimize the distance between objective and scheduled power load curve which ensures the minimization of electricity cost, appliance waiting time and PAR. The trade-off between cost and PAR is shown in Fig. 7.

Fig. 8 illustrates the power consumption pattern of each hour and objective load curve. It is clear from Fig. 8, MBHBCO scheduled load curve is closer to the objective load curve during the On-peak hours than the others techniques using all the taken electricity rate.

RTP has high price during the hours 8:00am to 2:00pm, Fig. 8(a) shows that during the peak pricing hours, scheduled

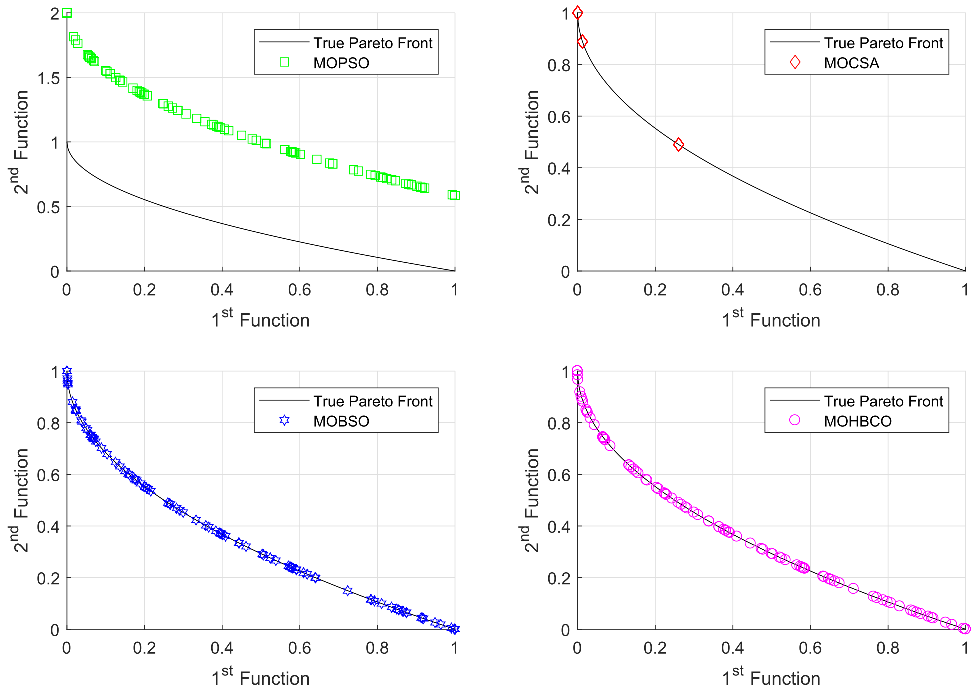


FIGURE 6. Bench-mark test function ZDT4 results for proposed and existing techniques.

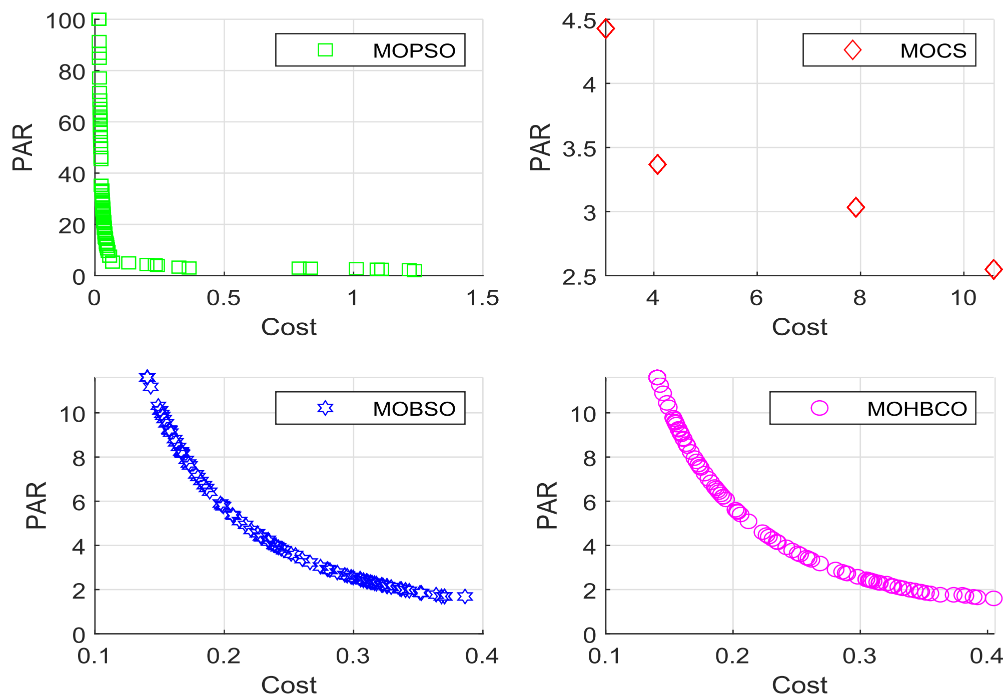


FIGURE 7. Trade-off between cost and PAR.

load of MBPSO, MBCSO and MBBSO is high; however, MBHBCO maintains the load below the objective load line.

Whereas, Fig. 8(b) shows that ToU has high rates during 7:00am to 5:00pm, and 7:00am-10:00am. These are shoulder-peak hours and all the scheduling schemes have load profiles greater than objective load curve which somehow increases the electricity cost during these hours as shown in Fig. 10(b). 11:00am- 4:00pm are critical hours of CPP, it has highest price rates on this time interval as demonstrated in Fig. 8(c) and the aggregated scheduled load by all the scheduling schemes is beneath the objective load curve. It is also noted that the distance between the scheduled load and the objective

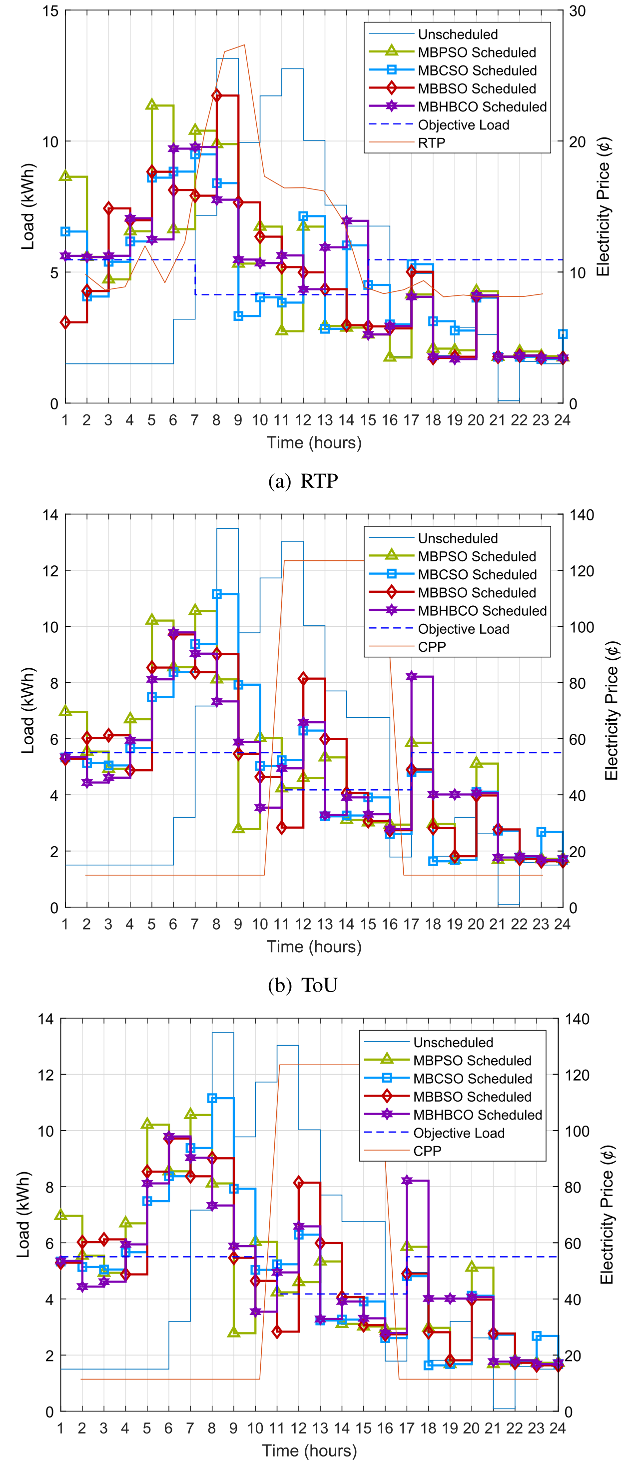
TABLE 3. Summary of results for MSE.

Test Functions	MOPSO	MOCSO	MOBSO	MOHBCO
	5 variables			
ZDT1	0.0016	0.0455	0.0026	0.002
ZDT2	0.002	0.3209	0.0027	0.0023
ZDT3	0.0052	0.0778	0.0025	0.0052
ZDT4	0.0081	0.1636	0.0059	0.0048
	10 Variables			
ZDT1	0.0019	0.0636	0.0020	0.0016
ZDT2	0.3542	0.3542	0.0032	0.0051
ZDT3	0.0086	0.1541	0.0017	0.0042
ZDT4	13.1523	0.2886	0.3189	0.0022

load curve is greater during the hour 8:00am as compared to other hours, it is because of maximum number of non-schedulable appliances which are turned ON by the user.

Electricity price of each hour is shown in Fig. 10 which is a direct reflection of Fig. 8, these figures reveal that the high energy consumption on On-peak hours increases the cost significantly. Figs. 10(a)- (b) illustrate that the electricity cost during the On-peak and Off-peak hours has almost the same pattern; however electricity load during On-peak hours is low as compared to Off-peak hours, this is because of double prices during On-peak hours. Fig. 10(c) reveal that prices during On-peak hours are high as compared to the Off-peak where load during these hours is low as shown in Fig. 8(c). The reason for this behaviour is that the price during the On-peak hour is 10.8 times greater than Off-peak hours. Additionally, Fig. 10 shows that the electricity consumption cost of scheduled load is less than the unscheduled load during the On-peak hours which shows that the overall electricity cost decreases after scheduling the electric appliances as illustrated in Table 4. This table demonstrates that MBCSO has reduced up to 21% of total electricity cost, whereas, MBPSO, MBBSO and MBHBCO reduce 18%, 15% and 18%, respectively as compared to unscheduled cost for RTP. For ToU tariff, among all scheduling techniques, MBBSO and MBHBCO outperformed with 22% and 23% decrement in electricity bill than unscheduled load cost, while MBPSO and MBCSO reduce the electricity cost up to 20% and 22%, respectively. Moreover, 77% highest reduction in electricity cost is observed for MBPSO as compared to the cost of unscheduled load. Moreover, 71%, 60% and 69% cost is reduced by MBCSO, MBBSO and MBHBCO, respectively.

The reduction of PAR is elucidated in Table 5. It reveals that the proposed technique MBHBCO outperforms the other techniques: MBBSO, MBPSO and MBCSO. Results in Table 5 shows PAR 6.58 for MBHBCO, this optimization technique has decreased 19% PAR, on the other hand, MBPSO, MBCSO, MBBSO decrease 3%, 11% and 6% for RTP, respectively. For ToU price tariff, best performance is shown by MBHBCO by reducing 27% in PAR, whereas, MOPSO reduces 12%, MOCSO and MBBSO reduce PAR 23% and 4.7%. Results for CPP show 18.98% reduction in PAR by hybrid scheme than unscheduled PAR, MBPSO, MBCSO, MBBSO reduce 2%, 1.2% and 3.7% of



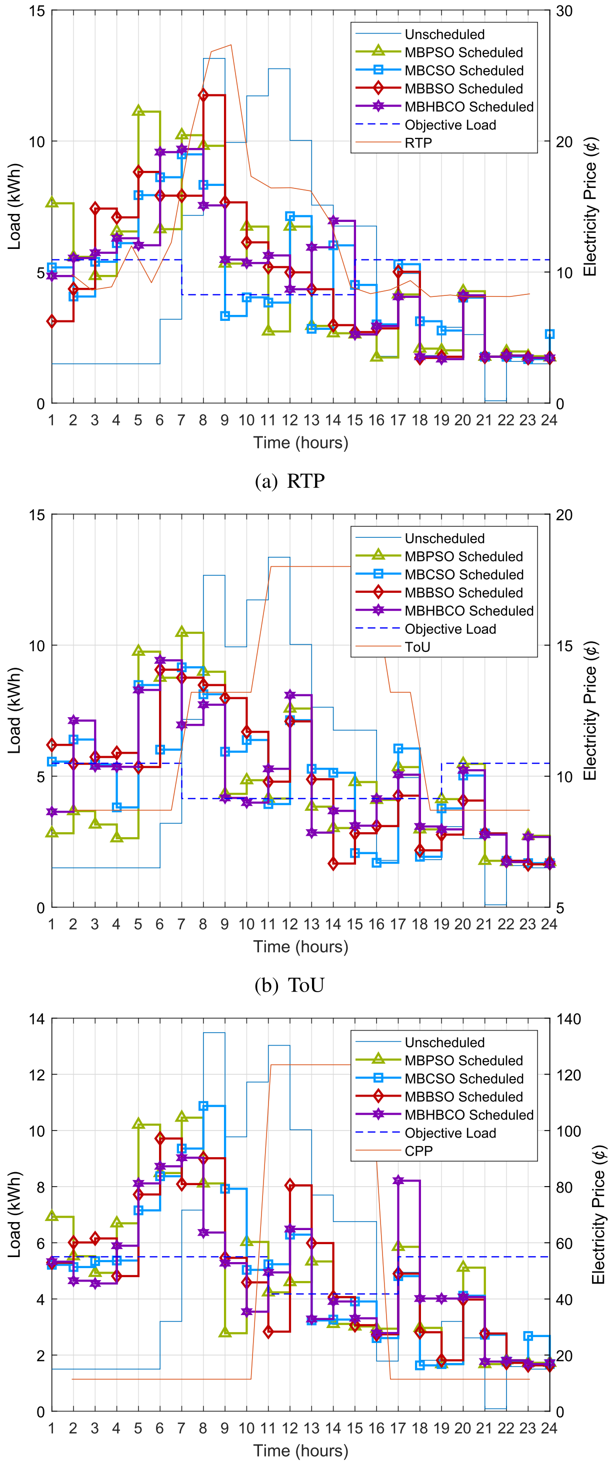
(a) RTP

(b) ToU

(c) CPP

FIGURE 8. Hourly power consumption details without real-time rescheduling along with three different pricing signals.

PAR, respectively. PAR of optimization techniques is almost same for RTP and CPP because at 7:00am most of non-schedulable appliances are turned ON by user, this behaviour can be seen in Fig. 8.

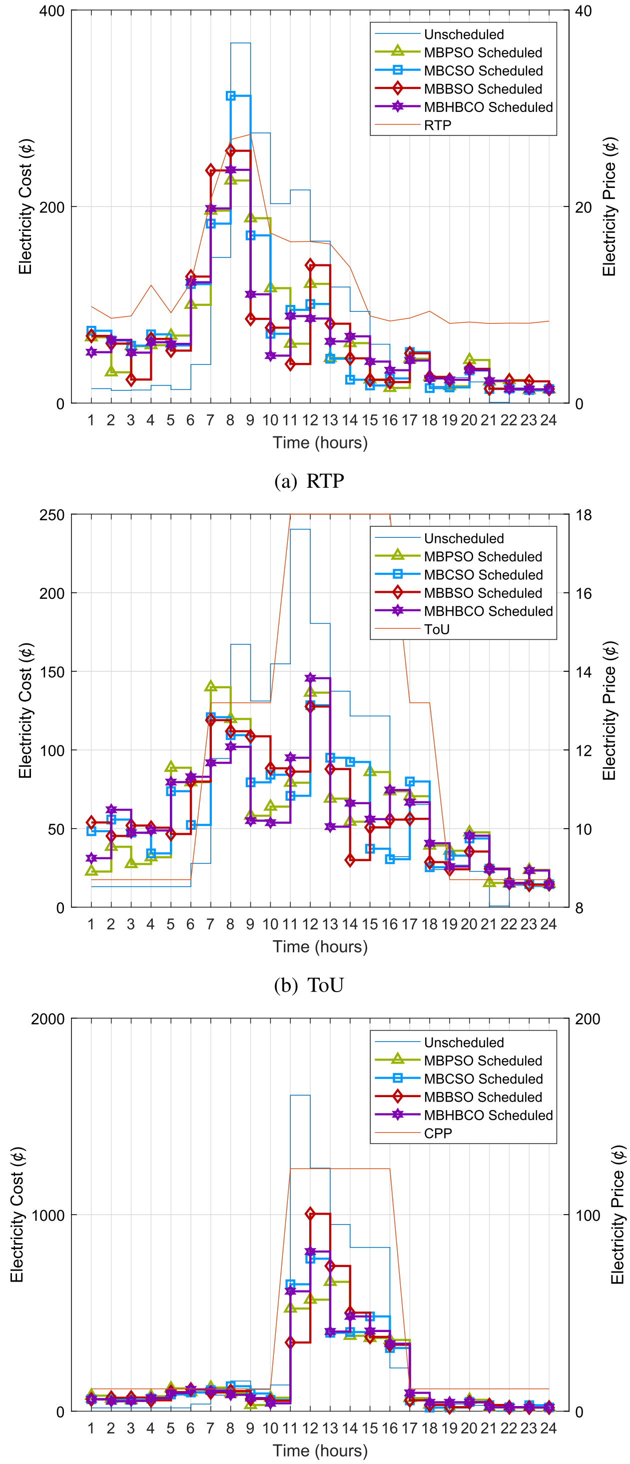


(a) RTP

(b) ToU

(c) CPP

FIGURE 9. **Effect of real-time rescheduling on power consumption for each hour during a day along three pricing signals.**



(a) RTP

(b) ToU

(c) CPP

FIGURE 10. **Per hour electricity cost details without real-time rescheduling along with three different pricing signals.**

It has been discussed in previous sections that the home energy management is a multi-objective problem and there is always a trade-off between electricity bill minimization and appliances waiting time and PAR and electricity bill minimization. Somehow, we try to optimize the system by using Pareto optimal method; however, still user must pay some cost in terms of waiting time while reducing the electricity bill. Fig. 12 illustrates group wise average waiting time for all three price tariffs. Fig. 12(a) demonstrates that MBHBSC, one of the proposed techniques has minimum average waiting time of 3 hours and the MBPSO technique

TABLE 4. Total cost of a day for day-ahead scheduling with and without coordination, and coordination based real-time scheduling for three different price tariffs.

Tariff	Unscheduled	MBPSO	MBCSO	MBBSO	MBHBCO
	Day-ahead Scheduling Cost Without Coordination				
RTP	1991	1629	1560	1689	1627
ToU	1730	1431	1410	1407	1398
CPP	6964	3927	4072	4329	4104
	Cost for Real-time scheduling With Coordination				
RTP	1991	1609	1535	1683	1600
ToU	1730	1402	1406	1420	1386
CPP	6964	3924	4064	4304	4063
	Day-ahead Scheduling Cost With Coordination				
RTP	1915	1553	1503	1492	1401
ToU	1657	1449	1456	1370	1288
CPP	6537	4480	3334	4342	4592

TABLE 5. Calculated PAR of a day for day-ahead scheduling with and without coordination, and coordination based real-time scheduling.

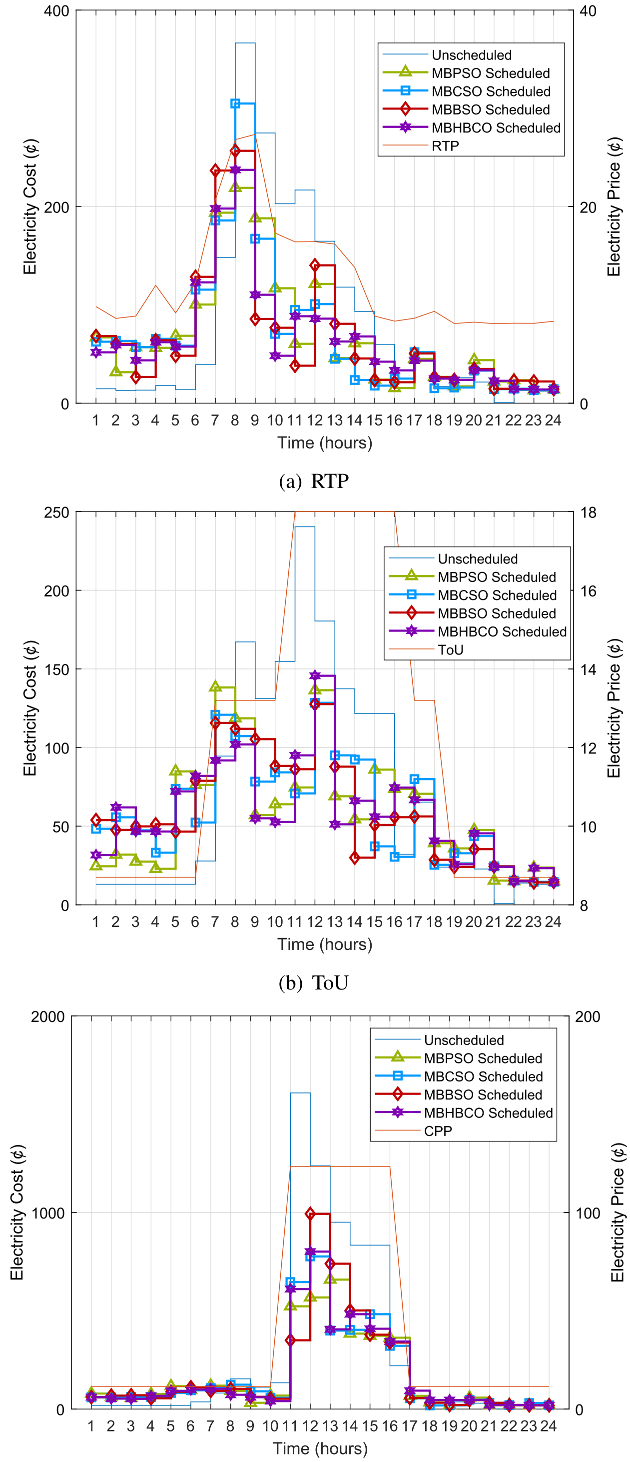
Tariff	Unscheduled	MBPSO	MBCSO	MBBSO	MBHBCO
	PAR Day-ahead Scheduling Without Coordination				
RTP	8.14	3.5	3.24	3.24	3.24
ToU	7.05	3.56	3.92	3.92	3.30
CPP	7.39	3.2	3.2	3.2	3.05
	PAR for Coordination based Real-time Scheduling				
RTP	8.14	3.61	3.59	3.44	3.52
ToU	7.05	3.55	3.44	3.6	3.46
CPP	7.39	3.36	3.29	3.56	3.17
	PAR for day-ahead Coordination				
RTP	8.193	3.53	2.54	3.54	2.32
ToU	8.05	3.56	3.44	3.22	3.46
CPP	8.51	4.5	3.6	3.46	3.46

shows 3.5 hours of highest waiting time. It can be visualized form this graph that there is not much difference between the waiting times of all scheduling techniques. For ToU pricing scheme, the highest waiting time is 3.5 hours, which is of hybrid technique and lowest waiting time 3.2 hours is obtained by MBBSO technique as shown in Fig. 12(b). Using CPP, the highest average waiting time of appliances is 3.4 hours by MBHBSC scheduler, where it is 3.3 hours by MBPSO and MBCSO which is minimum waiting time.

The overall discussion shows that the proposed hybrid technique outperforms other techniques except in term of waiting time, where MBHBCO has good results for ToU only. It is also analysed that whatever pricing technique is adapted, it does not affect the performance of our proposed multi-objective technique. This is because of our strategy to hybrid the technique that would effectively search and target global and local search space.

Furthermore, if we have a look on the per day cost of electricity in unscheduled case for three price tariffs: RTP, ToU and CPP, their cost is 1991 cents, 1730 cents and 6946 cents respectively. The unscheduled and the scheduled costs reveal that ToU is more economic than RTP. Moreover, if we analyse PAR which directly helps in reducing the cost, specially in case of RTP, where the load of each hour decides the price for the next hour.

In order to further authenticate the performance of the proposed techniques, we find the confidence interval of 95% for electricity cost and PAR. The upper and lower values



(a) RTP

(b) ToU

(c) CPP

FIGURE 11. Effect of real-time rescheduling on electricity bill for each hour during a day along with three pricing signals.

in Table 6 show the probability of true mean values between upper and lower values. The difference between upper and lower values shows the fluctuation in the results (i.e., maximum fluctuation with maximum difference). The table shows the different behaviour of optimization techniques for

TABLE 6. 95% confidence interval for different performance parameters.

Tariff	MBPSO		MBCSO		MBBSO		MBHBCO	
	Cost							
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
RTP	1472	1785	1455	1666	1583	1795	1533	1721
ToU	1375	1486	1364	1457	1360	1453	1314	1481
CPP	3504	4349	3014	5131	3500	5159	3438	4769
	PAR							
RTP	6.5	9.0	5.6	8.9	4.6	10.6	4.4	8.7
ToU	4.42	8.82	4.06	7.63	5.37	9.11	3.35	7.68
CPP	6.24	9.14	5.45	10.26	6.38	8.98	4.08	8.72

TABLE 7. Effects of coordination based real-time scheduling on different performance parameters.

Tariff	MBPSO	MBCSO	MBBSO	MBHBCO
	Cost			
RTP	1.2% decrease	1.6% decrease	0.35% decrease	1.65% decrease
ToU	2.02% decrease	0.28% decrease	0.92% increase	0.8% decrease
CPP	0.07% increase	0.19% decrease	0.5% decrease	0.99% decrease
	PAR			
RTP	0% increase	4.73% increase	1.82% increase	1.87% increase
ToU	7.4% increase	0.6% decrease	4.9% decrease	1.81% increase
CPP	0.5% decrease	6.5% decrease	1.31% increase	49.37% decrease

different situations. Minimum difference in upper and lower values of electricity cost is 15% with hybrid scheme for RTP. Whereas, for ToU, the minimum difference of 7% is observed with MBCSO and MBBSO; further, the MBPSO outperforms for CPP. In case of PAR, similar behaviour is observed. For RTP rates, MBCSO shows the highest performance, where MBBSO outperforms for ToU and CPP.

C. REAL-TIME SCHEDULING WHILE ASSIMILATING COORDINATION

Here, we discuss how the user's run-time interrupt effects the overall electricity consumption cost, PAR and waiting time. In the previous section, it is clearly elaborated that one of the system's objective is real-time scheduling according to the user's demand. When user requests to switch ON an appliance, a request is sent to the scheduler to reschedule the priority appliances.

Fig. 9 illustrates per hour power consumption pattern after real-time scheduling. For the simulation purpose of the real-time scheduling, we generate some interrupts randomly for the 24-hour time-slot where already defined schedule will be updated. We generate random interrupts during different hours in a day. In this way, minor difference is recorded and cannot be ignored. Somehow, as a result of real-time rescheduling, an increase or decrease in cost, PAR and waiting time is noticed and is given in Table 7. Fig. 9(a) for RTP signals shows the difference from Fig. 8(a) during 3:00am, 9:00am, 1:00pm, etc. Whereas, for ToU, Fig. 9(b), shows the difference from Fig. 8(b) during 4:00am, 8:00am, etc., moreover, CPP reveals the difference at 2:00am, 6:00am, etc., in distinction to 8(c). The power load profile consequences manifest in Fig. 11 and Table 4 and 5. Table 7 shows that the cost is decreased by 1.65% using MBHBCO while considering the coordination for RTP. Furthermore, the percentage difference between with and without coordination for ToU is observed as 2.02% decrease in electricity bill for MBPSO, 0.28% and 0.8% by MBCSO and MBHBCO, respectively. Whereas, 0.92% increase in electricity cost is observed for MBBSO. Total electricity cost for CPP according to different scheduling techniques is also shown in Table 7 which shows 0.07% minimum decrease in electricity cost by MBPSO scheduler. Whereas, highest decrease in cost is observed by MOHBCS which is 0.99% than that of without incorporation of real-time scheduling or coordination. After coordination, the overall cost is reduced; however, an increase in PAR is observed. As Table 7 illustrates that for RTP, MBCSO shows 5% decrement in cost. On the other hand, it has 11% increase in PAR which is highest one. This reveals the trade-off between cost and PAR. Similar behaviour is observed for ToU price tariff as depicted in Table 7, it has 4.73% higher increase in PAR with coordination. Whereas, 1.31% increase is observed by MBBSO in case of CPP.

The main target of real-time rescheduling through coordination is user comfort maximization. From this discussion, it is clear that there is always a trade-off between different performance parameters. In this regard, we have discussed trade-off between total cost and PAR, and waiting time and cost. Figs. 8 and 9 show that our defined fitness function helps to maintain the low electricity load profile during the On-peak hours which eventually helps in reducing the electricity bill and also its balanced nature helps in minimizing the PAR. Somehow user has to wait for appliance to start working. Moreover, our next main objective: real-time rescheduling, enables the system to turn OFF and ON an appliance on the request of a user. It does not show much fluctuation in cost and PAR; however, it reduces the waiting time.

D. COORDINATION BASED DAY-AHEAD SCHEDULING

In the previous sections, day-ahead scheduling without coordination and effect of real-time user demand on cost, waiting time and PAR are studied through simulations. From the simulation results, it is observed that real-time scheduling

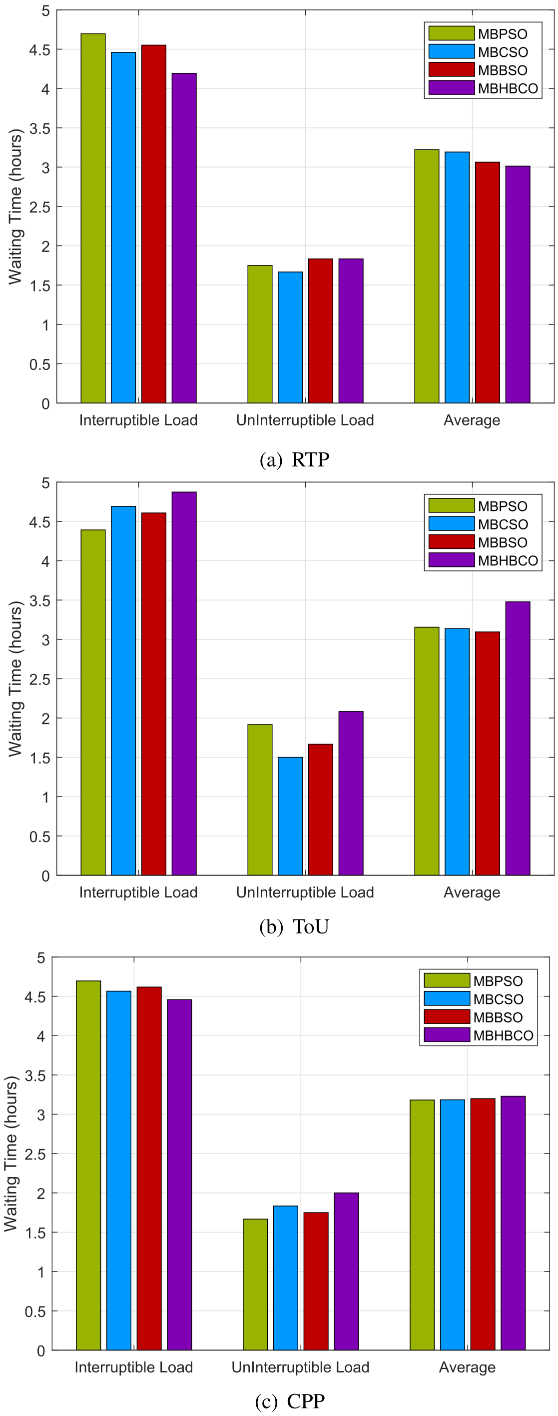


FIGURE 12. Group wise average waiting time of electric appliances without coordination.

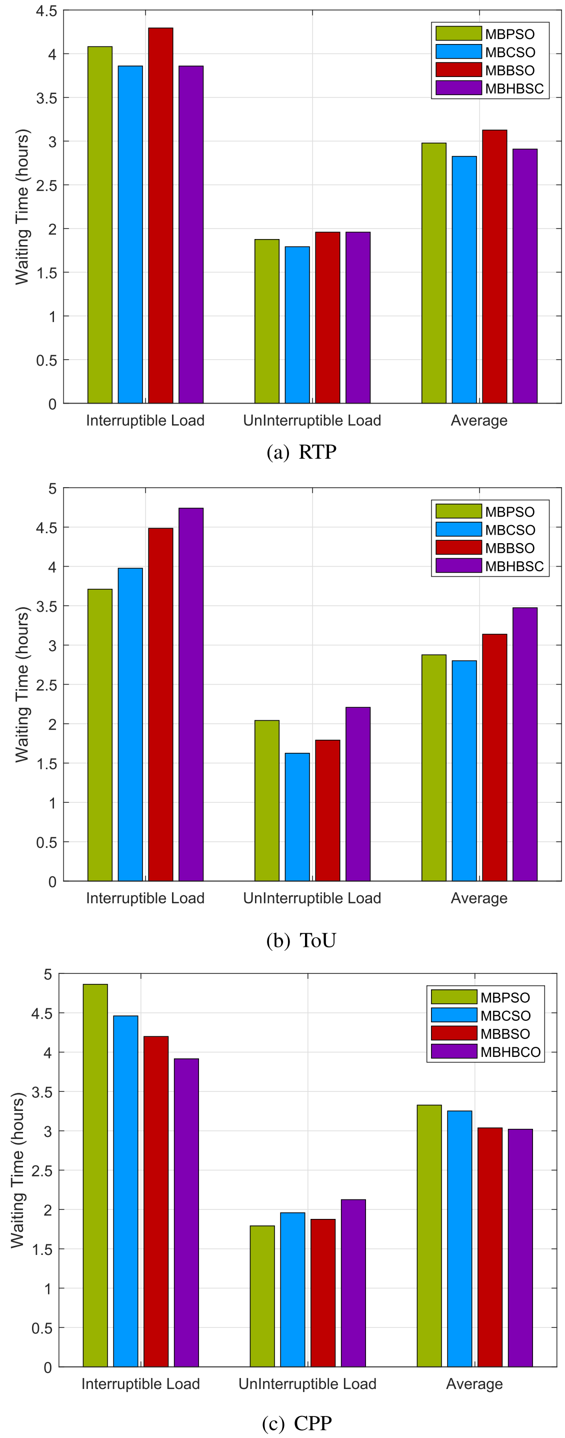
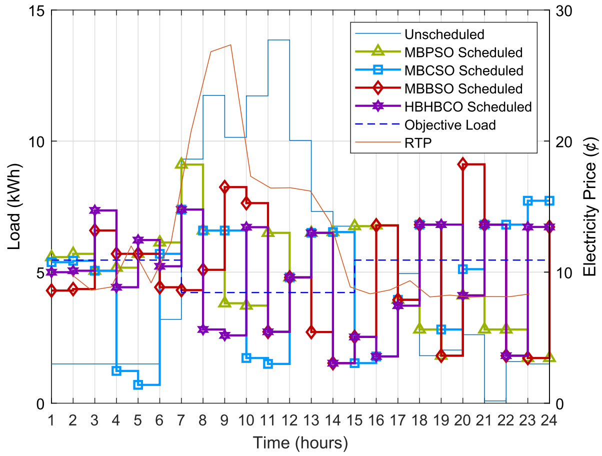


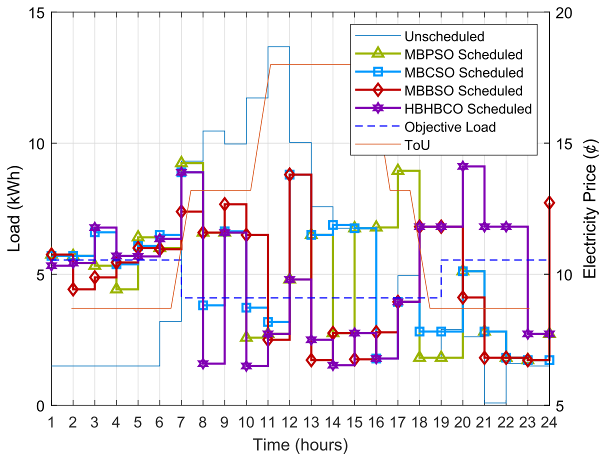
FIGURE 13. Coordination effect on average waiting time of group of electric appliances.

does not affect the cost and PAR. Further, the simulations are done for day-ahead scheduling through coordination. The simulation results show that in coordination based scheduling, users' demanded load is more close towards the objective load curve which directly affects the cost and PAR.

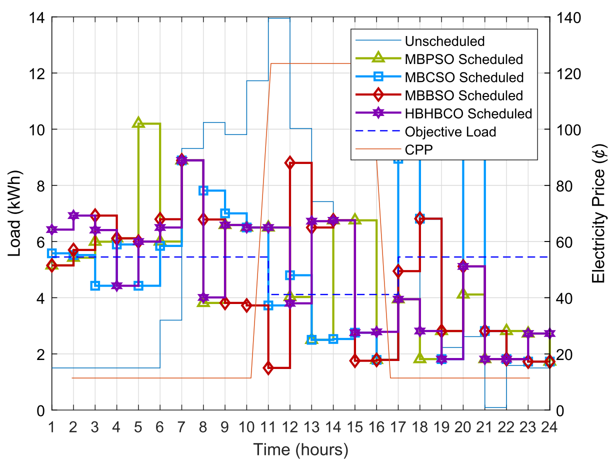
It can be clearly seen from Figs. 8, 10, 14 and 15 that the scheduled load is maintained towards the objective load curve, which eventually helps in reducing the electricity cost and price. Further, it can be observed from Fig. 14 (a) that other techniques somehow manage to maintain the objective load line except MBCSO and MBBSO. Whereas, in case of ToU and CPP tariff, our proposed schemes MBBSO and MBHBCO outperform MBPSO and MBCSO. Moreover, the tabular results in Table 4 show minimum



(a) RTP

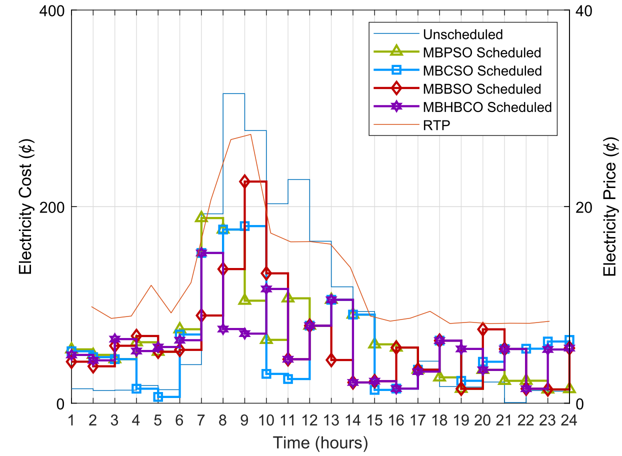


(b) ToU

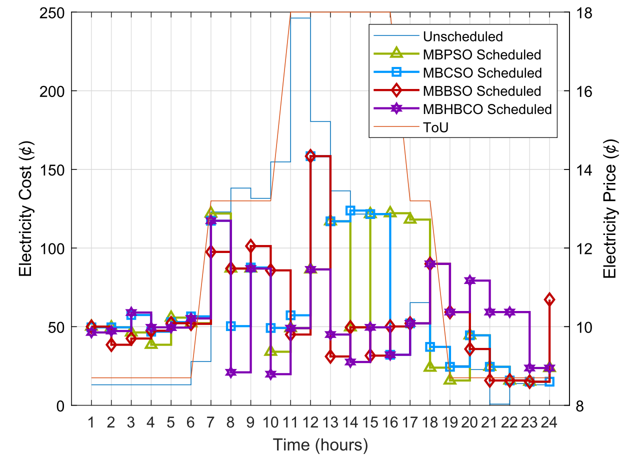


(c) CPP

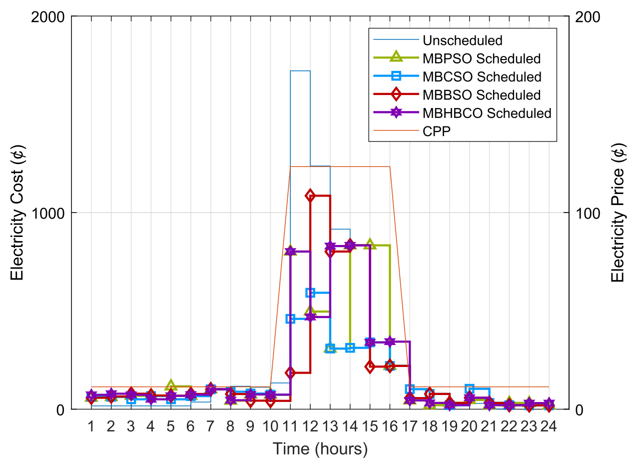
FIGURE 14. Day-ahead coordination effect on hourly power consumption along with three different pricing signals.



(a) RTP



(b) ToU



(c) CPP

FIGURE 15. Effect of day-ahead coordination electricity cost for each hour during a day along three pricing signals.

cost, i.e., 1432 cents for RTP with MBPSO, 1288 cents for MBHBCO using ToU; whereas for CPP, best performance is achieved by MBCSO. MBCSO shows minimum PAR 3.44, 3.22 and 3.46 for RTP, ToU and CPP, respectively and shown in Table 4.

In this research work, the proposed MBBSO and MBHBCO are designed for HEMS. Due to meta-heuristic generic behaviour, these presented algorithms can be applied on any optimization problem. Also, after omitting binary conversion process, these techniques are also applicable on any non-binary optimization problem, as deliberated in experimental results given in Fig. 3-6 and Table 3.

VI. CONCLUSION

This paper proposes the single and multi objective based models for day-ahead (with and without coordination) and real-time appliances scheduling. For home load scheduling, conflicting objectives are: minimization of electricity bill, waiting time reduction and PAR minimization. This is possibly implemented through non-dominated Pareto front based solutions that are obtained from the search space provided by MBBSO and MBHBCO for day-ahead scheduling. To analyse the performance of the proposed schemes, the results are compared with well-known existing techniques such as MBPSO and MBCSO. On contrary, the single-objective problem targets to maintain flexibility in order to incorporate the coordination. This real-time rescheduling reduces the waiting time of rescheduled appliances. Additionally, to check the compatibility and generic behaviour of these proposed techniques, simulation results are evaluated using three electricity tariffs namely RTP, ToU and CPP. Simulation results show that changing pricing schemes do not show any prominent effect on the system's performance. On the other hand, dynamic programming based algorithm is proposed for day-ahead and real-time scheduling. Results reveal that coordination based day-ahead scheduling is more effective in reducing the electricity cost and PAR as compared to without coordination. Moreover, after rescheduling, fluctuation in PAR and electricity cost patterns is not noticeable, this is because of balanced scheduling using objective load curve and coordination using dynamic programming. Moreover, further experiments are also being conducted in order to validate the proposed algorithms. The comparative study on four well known bench-mark functions has proven the effectiveness of proposed techniques. Further, it is observed that main drawback of MOPSO is premature convergence; whereas, MOCSO is trapped in global optima. In addition, the proposed techniques have ability to strive in both local and global optima.

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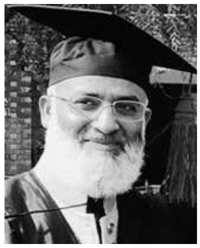

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