Optimal Scheduling of Grid Transactive Home Demand Responsive Appliances Using Polar Bear Optimization Algorithm

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ABSTRACT The conventional power system has been evolving towards a smart grid system for the past few decades. An integral step in successful realization of smart grid is to deploy renewable energy resources, particularly rooftop photovoltaic systems, at smart homes. With demand response opportunities in smart grid, residential customers can manage the utilization of their demand responsive appliances for getting economic benefits and incentives in return. In this regard, this paper proposes an effective home energy management system for residential customer to optimally schedule the demand responsive appliance in the presence of local photovoltaic and energy storage systems. For efficient home-to-grid energy transactions in home energy management system, the stochastic nature of photovoltaic power generation is modeled with the beta probability distribution function for solar irradiance. The main contribution of this paper is the application of polar bear optimization (PBO) method for optimally solving the scheduling problem of demand responsive appliances in home energy management system to minimize electricity consumption cost as well as peak-to-average ratio. The effectiveness of the proposed metaheuristic optimization technique is proven by performing different case studies for a residential consumer with different base load, uninterruptible deferrable, and interruptible deferrable appliances under a real-time energy price program. Comparative results with different metaheuristic techniques available in the literature show that the electricity consumption cost and peak-to-average ratio are effectively optimized using the proposed PBO algorithm.

INDEX TERMS Demand response, home energy management system, metaheuristic optimization, photovoltaic generation, polar bear optimization, smart appliances.

I. INTRODUCTION

The current electric power system is moving toward smart grid system due to increasing integration of distributed energy resources, particularly renewable energy resources (RERs) and energy storage systems (ESSs), smart sensors, and smart meters [1]. All these generation, storage, monitoring, and control devices and systems are necessary for the successful realization of smart green electric power system for achieving energy conservation and climate change mitigation goals. Smart grid is essential for providing emission-free electric power generation and consumer-oriented energy conservation policies to achieve environmental sustainability, electric power supply reliability, and consumer comfort ability [2].

Residential loads have significant contribution in the total power demand of national electric power system. In [3], it is estimated that residential load consumes 30-40% of total electric power supply generation. Therefore, smart homes need to be efficiently coordinated with energy utilities and market operator for efficient operation of microgrids and smart grid [4]. Energy management systems can help in efficiently managing the load demand of smart homes [5], smart buildings [6], and microgrids [7] to reduce grid electric power generation during peak demand periods. The advancements in communication and control technologies has paved
way for home energy management system implementation in smart home and smart buildings for optimally managing their electricity consumption. The effective coordination among utilities and smart residential houses energy management systems (HEMSs) also helps in reducing electricity consumption cost (ECC) [8].

Different electricity tariff methods are introduced for encouraging consumers in reducing their electricity consumption [9], [10]. Both supply and demand side managements are performed in smart grid operation, where supply side management involves generation, transmission, and distribution system management and demand side management involves load management at consumer end using load shedding and demand response (DR) methods. DR programs help residential consumers in shifting, controlling, and interrupting their domestic appliances for economic benefits and smart grid for stable and reliable operation of electric power system.

DR programs schedule demand responsive appliances (DRAs) operation of residential customers from peak price periods to low price ones to achieve objectives of minimizing electricity consumption cost and peak-to-average ratio (PAR). With efficient DR program, residential customers help in improving energy efficiency of distribution system and smart grid to avoid blackouts, reliability, and stability problems. DR programs are broadly classified into two main type: price-based and incentive-based DR. Price-based DR program have different types like time-of-use price, critical peak price, real-time price, and peak-time rebate. Similarly, incentive-based DR includes direct-load control, demand bidding, and uninterruptible program methods. This paper focuses on price-based DR method for appliances scheduling using electricity price information obtained from smart meters.

Many researchers have worked on solving the challenging problem of optimal scheduling of DRAs. The ECC minimization is the main objective in home energy management scheduling problem, while also ensuring supply demand balance. Various solution methods have been proposed by researchers to achieve objectives of electric energy consumption cost-minimization, consumer comfort maximization, and PAR reduction.

The DRAs optimal scheduling problem is a discrete multi-dimensional nonlinear problem with associated constraints. Several classical and metaheuristics solution methods, such as mixed-integer programming, rolling optimization, particle swarm optimization (PSO), grey wolf optimization (GWO), genetic algorithm (GA), and bat algorithm among others, have been proposed in the literature for solving DRAs scheduling problem [5].

A mixed-integer programming-based optimal scheduling of DRAs was proposed in [11] for reducing ECC, environmental emissions, and energy import from main grid. In [12], a mixed-integer linear programming method was used to solve DRAs optimal scheduling problem to minimize ECC and PAR for residential customers. The customers’ comfort objective was introduced in [13], and proposed scheduling problem was solved by heuristic method.

In [14], a mixed-integer linear programming (MILP) model was developed for the optimal and stochastic operation scheduling of smart homes as well as smart buildings. The aim of the authors developed model was to match the electricity demand with the intermittent solar-based renewable resources profile and to minimize the energy cost.

A multi-objective HEMS problem was developed in [15] to minimize ECC and reduce peak load demand using time-of-use energy price program. The developed multi-objective problem was solved using mixed-integer linear programming method. However, the developed model had not considered RERs integration in home EMS model. In [16], an intelligent HEMS was developed for optimal scheduling of DRAs using PAR and electricity buying tariff. However, integration of RERs and ESSs into HEMS was not considered.

In [17], an effective energy management system (EMS) for application in integrated building was introduced and implemented as a multi-objective optimization problem. The proposed architecture covered different key modeling aspects such as distributed heat and electricity generation characteristics, heat transfer and thermal dynamics of sustainable residential buildings and load scheduling potentials of household appliances with associated constraints.

An ontology-driven multi-agent based EMS was proposed for monitoring and optimal control of an integrated homes/buildings and microgrid system with various RERs and controllable loads. Different agents ranging from simple-reflex to complex learning agents are designed and implemented to cooperate with each other to reach an optimal operating strategy for the mentioned integrated energy system while meeting the system objectives and related constraints [18].

An HEMS was proposed in [19] for minimizing ECC for residential consumers and GA method was used to solve the proposed HEMS. Evolutionary algorithm was presented in [20] for solving energy scheduling optimization problem of residential area by managing appliances operation in suitable time periods to minimize ECC. However, RERs are taken into consideration. In [21], [22], PSO method was used for optimizing HEMS energy scheduling. A binary PSO algorithm was proposed in for optimally shifting the DRAs operation from high to low energy price periods. PSO performs better in continuous optimization problem, but it suffers from local optima issue in discrete optimization problems. Therefore, PSO is not an appropriate solution for HEMS problem due to its discrete model nature [23].

An optimal DRAs scheduling was solved using electron drifting algorithm for minimizing ECC and environmental emissions [24]. The electron drifting algorithm has low probability of convergence to local optimum solution. However, it suffers from lack of constraints handling explicit rules, resulting in high uncertainty in its practical implementation. In [25], performances of cuckoo search, binary PSO, and GA algorithms were compared for HEMS, which includes
DRAs, RERs, and ESSs. The objective was ECC and PAR minimization under time-of-use energy price scheme.

In [26], a novel operational model was proposed for the interconnected microgrids in the transactive energy market. The full clean energy production goal was realized by equipping each microgrid with RERs and ESSs only.

Dijkstra algorithm was proposed in [27] for achieving efficient DRAs scheduling with reduced system complexity. However, RERs and ESSs were not taken into consideration. A GA-based evolutionary algorithm was presented in [28] for minimizing ECC of residential sector using ESS in a smart grid environment. However, investment cost of ESS was not taken into consideration. The supply demand balance was achieved in [29] for residential, commercial, and industrial users using GA algorithm. The demand side management with GA performs better than simple demand side management. However, PAR objective was not considered.

A residential demand side management with RERs integration was presented in [30]. The day-ahead price was used for optimally scheduling the DRAs using GA algorithm with objectives of ECC minimization and PAR reduction. A non-dominated sorting GA was proposed in [31] for optimally scheduling DRAs to minimize ECC and reduce PAR. The real-time energy prices were used with inclined block rate to avoid increasing peak demand during low-energy price periods. GA, cuckoo search, and crow search-based metaheuristic algorithms were presented in [32], which minimize ECC and reduce PAR of residential consumers. However, RERs were not integrated in the developed model.

A convex smart home scheduling model was developed in [33] to minimize ECC and reduce PAR using real-time energy price program. In [34], a fuzzy logic-based scheduling model was proposed for maintaining supply demand balance by efficiently scheduling DRAs, RERs, and ESSs. An optimal HEMS was developed in [35] for optimized DRAs, RERs, and ESS scheduling using enhanced differential evolution, GWO, and their hybrid evolutionary algorithm to minimize ECC and PAR under real-time energy prices.

A mixed-integer nonlinear programming-based energy scheduling was developed in [36] for minimizing ECC of residential consumers under time-of-use energy prices. A mixed-integer linear programming model was presented in [37] for optimally scheduling DRAs to minimize ECC. The power supply demand balance was achieved after DRAs scheduling. In [38], a dynamic programming method was proposed for DRAs scheduling with predefined time-intervals and preferences of smart appliances. The objective was minimization of ECC by shifting DRAs from high to low energy price periods according to defined preferences.

It can be summarized from the above-discussed literature that HEMS has been optimally solved using different algorithms: mixed-integer linear and non-linear programming, electron drifting algorithm, PSO, convex programming, dynamic programming, GA, cuckoo search algorithm, score-based HEMS algorithm, Dijkstra algorithm, and integer linear programming. Nevertheless, in some cases, these algorithms suffer from either low convergence rate with local optimum solution or low capability to deal with volatile nature of different DRAs. Moreover, RERs and ESS integration, customer comfort, and dynamic pricing-based practical constraints have been rarely considered in the literature for DRAs scheduling. Furthermore, the aforementioned HEMS models have considered deterministic modeling of RERs. However, RERs, particularly solar and wind, are intermittent in nature and their power generations involve variability and uncertainty. Such uncertain energy productions of RERs are modeled using stochastic or probabilistic methods.

Therefore, this paper presents PV and ESS integrated optimal HEMS model, which includes probabilistic modeling of PV power generation and real-time energy prices. The HEMS objective is ECC minimization and PAR reduction. The HEMS is solved for determining optimal DRAs scheduling using three different metaheuristic algorithms: GWO, GA, and proposed Polar Bear Optimization (PBO) method under real-time pricing scheme. The contributions of this papers are as follows:

- The application of PBO algorithm for optimally solving the DRAs scheduling problem.
- The integration of probabilistic modeling of PV power generation in DRAs scheduling problem.
- The analysis of real-time pricing scheme using the proposed HEMS model for DRAs optimal scheduling.

The rest of the paper is organized such that section II presents HEMS architecture and appliances modeling along with PV and ESS modeling. Section III explains problem formulation for optimal DRAs scheduling. Section IV explains polar bear optimization algorithm. Section V describes case study and section VI presents results and discussion followed by conclusion in Section VII.

II. HEMS ARCHITECTURE AND MODELING

The HEMS architecture contains smart meter, energy management controller (EMC), power electronic converter, display system, ESS, PV system, and a set of appliances, which are shown in Figure 1 [39]. The inverter and rectifier operations are performed by power electronic converter. In this mechanism, the ESS, PV system, and smart appliances shared information with EMC using a a wireless system. The smart meter receives real-time energy price signal through an advanced metering infrastructure (AMI) and shares information with EMC. The EMC receives information of tariff signal and user-defined DRAs operating preferences, which are fed to metaheuristic optimization algorithms to determine the optimal DRAs scheduling such that ECC and peak demand reduction objectives are achieved. The optimal results are sent to EMC for communicating these references to DRAs for taking necessary actions in implementing the results without compromising the customer’s comfort. The home energy transaction with grid is assumed to be achieved through smart meter. These types of tariffs are normally termed as net-billing or net-metering.
appliances are scheduled for are denoted by \( X \) categorized into three different classes. In these classes, base load appliances (BLAs), interruptible deferrable appliances, and uninterruptible deferrable appliances (UDAs) are included. The total consumer appliances are represented by set \( X = \{X_{bs}, X_{id}, X_{ud}\} \). The set of BLAs, IDAs, and UDAs are denoted by \( X_{bs}, X_{id}, \) and \( X_{ud} \), respectively. All home appliances are scheduled for \( N \)-hours duration according to defined user preferences and the value of \( N \) is taken as 24 in the case study. The \( N \)-hours time duration set is expressed as,

\[
t \in T = \{1, 2, 3, \ldots, N\}
\] (1)

Each consumer appliance should be operated within the initial starting time, \( t_{s,bs} \), and smallest finishing time, \( t_{e,bs} \). The difference between the initial starting time and the actual starting time, \( t_{s,bs} \), of the appliance is identified as the waiting time of that particular appliance. \( t_{s,bs} \) and \( t_{e,bs} \) for each appliance are defined according to consumer preferences, and they are provided in Table 1. The proposed DRAs scheduling problem uses twelve different appliances that are considered as a case study.

1) BASE LOAD APPLIANCES
BLAs belong to the first group of appliances and they act as critical load in a smart home. These appliances operation cannot be adjusted. Consumers have their own preferences of fixing their start and finishing time. Each BLA is represented as \( x_{bs} \in X_{bs} \). The total energy consumed by BLAs at time instant, \( t \), is expressed by \( E_{bs}(t) \) in (2).

\[
E_{bs}(t) = \sum_{x_{bs} \in X_{bs}} P_{x_{bs}} \delta_{x_{bs}}(t)
\] (2)

where \( E_{bs}(t) \) is total energy consumption of BLAs at time \( t \). \( P_{x_{bs}} \) is power of BLA \( x_{bs} \). \( \delta_{x_{bs}}(t) \) represents operating status of BLA \( x_{bs} \) at time \( t \).

2) INTERRUPTIBLE DEFERRABLE APPLIANCES
IDAs are those consumer appliances that can be shifted or interrupted in any permissible time slot, defined by consumer, for accomplishing the optimum scheduling of appliances in a smart home. An IDA is expressed as \( x_{id} \) such that \( x_{id} \in X_{id} \). The total energy used by IDAs at time instant, \( t \), is determined by (3).

\[
E_{id}(t) = \sum_{x_{id} \in X_{id}} P_{x_{id}} \delta_{x_{id}}(t)
\] (3)

where \( E_{id}(t) \) is total energy consumption of all IDAs at time \( t \). \( P_{x_{id}} \) is power of IDA \( x_{id} \). \( \delta_{x_{id}}(t) \) represents operating status of IDA \( x_{id} \) at time \( t \).

3) UNINTERRUPTIBLE DEFERRABLE APPLIANCES
UDAs are those consumer appliances that can be deferred but can not be interrupted once they start operating. However, such type of appliances can shift their operation in defined time slots as long as they complete their operation before or at the end of their defined finishing time. The UDA is represented by \( x_{ud} \) such that \( x_{ud} \in X_{ud} \). The total energy utilized by this group of appliances at time instant, \( t \), is obtained by (4).

\[
E_{ud}(t) = \sum_{x_{ud} \in X_{ud}} P_{x_{ud}} \delta_{x_{ud}}(t)
\] (4)

where \( E_{ud}(t) \) is total energy consumption of all UDAs at time \( t \). \( P_{x_{ud}} \) is power of UDA \( x_{ud} \). \( \delta_{x_{ud}}(t) \) represents operating status of UDA \( x_{ud} \) at time \( t \).

B. ESS MODELING
ESSs are playing an important role in achieving green energy goals and ensuring the system reliability. Therefore, in our considered HEMS scheme, an ESS is used for storing excess available energy. The energy stored in the battery in any time instant, \( t \), is denoted by \( E_{b}(t) \) and given in (5). \( E_{b}(t) \) has positive value in case of charging, while it gets negative value during discharging. The charging and discharging efficiencies of the battery are denoted by \( \eta^{c} \) and \( \eta^{d} \), respectively. The constraints given in (6) and (7) are considered for limiting the maximum charging and discharging states of battery. \( \delta_{b}(t) \) is a binary variable at time \( t \), which determines battery discharging state (\( \delta_{b}(t) = 0 \)) and charging state (\( \delta_{b}(t) = 1 \)) at time \( t \).

\[
E_{b}(t) = \frac{E_{b}^{c}(t)}{\eta^{c}} \delta_{b}(t) - E_{b}^{d}(t) \eta^{d} (1 - \delta_{b}(t))
\] (5)

\[
0 \leq E_{b}^{c}(t) \leq E_{b, max}^{c}(t) \delta_{b}(t)
\] (6)

\[
0 \leq E_{b}^{d}(t) \eta^{d} \leq E_{b, max}^{d}(t) (1 - \delta_{b}(t))
\] (7)

\[
SOC(t) = SOC(t-1) + \frac{E_{b}(t)}{C_{b}}
\] (8)
The battery state of charge (SOC) characteristics are modeled in (8). Equation (9) models the minimum and maximum SOC limits of battery at time \( t \). \( C_b \) is battery rated capacity.

\[
SOC_{\text{max}} \leq SOC(t) \leq SOC_{\text{min}} \tag{9}
\]

The mathematical expressions of \( E_{\text{bu}}(t) \) and \( E_{\text{ud}}(t) \) are provided in (2), (3), and (4), respectively.

\[
E_{\text{bu}}(t) = E_{\text{bu}}(t) + E_{\text{id}}(t) + E_{\text{ud}}(t) \tag{15}
\]

where \( E_{\text{ir}}(t) \), \( E_{\text{pp}}(t) \), and \( E_b(t) \) are the total energy transacted with main grid, PV energy generation, and the battery charge (discharge) energy at time \( t \), respectively. A positive and negative value of \( E_b(t) \) represent the charging and discharging state of the battery, respectively.

\[
\begin{align*}
C_b = \sum_{t=1}^{N} E_{\text{ir}}(t) [\pi^+(t)\delta(t) +\pi^-(t)(1-\delta(t))] \tag{17}
\end{align*}
\]

\[
\begin{align*}
 PAR = \frac{\max(E_{\text{ir}})}{\frac{1}{N}\sum_{t=1}^{N} E^{\text{usc}}_{\text{ir}}(t)} \tag{18}
\end{align*}
\]

where \( E_{\text{ir}} = \{E_{\text{ir}}(1), E_{\text{ir}}(2), \ldots, E_{\text{ir}}(N)\} \). \( E^{\text{usc}}_{\text{ir}}(t) \) represents the energy demand from grid without deploying proposed metaheuristics algorithms in EMC.
E. APPLIANCE SCHEDULING PROBLEM FORMULATION

For the appliance scheduling problem, the main objectives are to minimize the electrical energy consumption cost and reduce the PAR, which were concisely highlighted in the introduction section. The objective function of the proposed scheme for the residential appliance scheduling problem can be mathematically expressed as:

$$\min(C_h, \text{PAR})$$

subject to:

$$|E_{gt}(t)| \leq E_g(t), \quad \forall t$$

$$\sum_{i \in T} \sum_{x \in X} E_{zx}(t) = \sum_{i \in T} \sum_{x \in X} E_{zx}(t)$$

IV. POLAR BEAR OPTIMIZATION ALGORITHM

In 2017, Dawid Połap and Marcin Woźniak [42] presented polar bear optimization algorithm, which is a nature inspired metaheuristic intelligent swarm optimization algorithm. The hunting behavior of polar bear has been mathematically modeled by the following four steps:

- Initial population;
- Global search using ice floes;
- Local search;
- Dynamic population control.

A. INITIAL POPULATION

First randomly generate initial population of polar bear and then find best solution in search space using exploration, exploitation, and dynamic population search mechanism. Each polar bear having z coordinates is represented as \( Y = (y_0, y_1, y_2, \ldots, y_{z-1}) \). At \( i_{th} \) iteration, a set of \( p \) polar bears having j coordinates can be denoted by \((Y^j)^{(p)}\).

B. GLOBAL SEARCH USING ICE FLOES

A hungry bear normally searches his local area to find something to eat. In case of food shortage, he moves to large stable ice floe. Ice floe should bear his weight for longer time duration, while searching for food, polar bear drifts the ice floe to the locations, where probability of finding seals for hunting is high. The drifting straightly moves towards the current optimum solution in initial population. This behavior has been mathematically modeled as:

\[
(Y^j)^{(p)} = ((Y^{j-1})^{(p)} + \text{sign}(v)\alpha + \rho
\]

where \((Y^j)^{(p)}\) represents \( p_{th} \) bear motion at \( j \) coordinates in \( i_{th} \) iteration towards the optimum. \( v \) represents the distance between the current and optimum polar bears. \( \alpha \) is a random number such that \( \alpha \in (0, 1) \). Finally, \( \rho \) is a random number varying between zero and \( v, \rho \in (0, v) \). The Euclidean metrics is used for computing distance between points \( Y^{(i)} \) and \( Y^{(j)} \) and it is written as:

\[
d(Y^{(i)}, Y^{(j)}) = \sqrt{\sum_{k=0}^{z-1} (Y^{(i)}_k - Y^{(j)}_k)}
\]

C. LOCAL SEARCH

During local search, the polar bears slowly move asymmetrically in arctic region to hunt the prey. The polar bears can approach their prey either on land surface, over ice or under the water. Seals most often like to stay on the floe. When they feel any danger they jump into the water. Swimming and diving are additional characteristics of polar bears. Polar bears can swim hundred kilometers/sixty miles without taking rest, which makes them one of the largest and deadliest non-aquatic predators in arctic region. During hunting, they jump into the water without any hesitation to capture the prey. In case of spotting seal, polar bear silently encircle the seal. Then he moves swiftly to catch the prey and quickly controls the victim by their stabbing teeth into the body of the prey. After capturing prey, he takes it out of the sea water onto the iceberg surface where he eats it. This behavior of polar bears is modeled using trifolium equation. This equation consists of two variable parameters: \( \theta_0 \) is the angle of tumbling, a random number from \((0, \pi/2)\) and \( \beta \in (0, 0.3) \) is polar bear vision range. The radius of polar bear vision is calculated in (24) using these two variable parameters.

\[
r = 4\beta \cos \theta_0 \sin \theta_0
\]

The individual movements are described by the following system of equations for each spatial coordinate.

\[
\begin{align*}
    y_0^{new} &= y_0^{old} \pm r \cos(\theta_1) \\
    y_1^{new} &= y_1^{old} \pm [r \sin(\theta_1 + r \cos(\theta_2))] \\
    y_2^{new} &= y_2^{old} \pm [r \sin(\theta_1 + r \sin(\theta_2) + r \cos(\theta_3))] \\
    \vdots \\
    y_{z-2}^{new} &= y_{z-2}^{old} \pm \left[ \sum_{k=1}^{z-2} r \sin(\theta_k + r \cos(\theta_{k-1})) \right] \\
    y_{z-1}^{new} &= y_{z-1}^{old} \pm \left[ \sum_{k=1}^{z-2} r \sin(\theta_k + r \sin(\theta_{k-1})) \right]
\end{align*}
\]

where \( \theta_1, \theta_2, \ldots, \theta_{z-1} \) are random numbers with uniform distribution from \((0, \pi)\) for \( z \) coordinates of each solution. We update the local position of bears by computing above equation by putting (+) sign and comparing fitness. If it is less than the original one, the sign is replaced by (−) and process is repeated until the best solution is found.

D. DYNAMIC POPULATION CONTROL

In PBO algorithm, 75% of total population is randomly initialized whereas the remaining 25% population growth depends upon the reproduction of the best and starvation of worst individuals among the population. PBO controls the population in each iteration such that the individual can be destroyed due to harsh arctic region. A constant \( \gamma \) is introduced to decided whether an individual can die or reproduce. \( \gamma \) is a random number, which lies in range \( \gamma \in [0, 1] \). The effect of harsh arctic region and dynamic population of this
algorithm can be mathematically modeled as,
\[
\begin{cases} 
\text{Reproduction}, & \text{if } \gamma > 0.75 \\
\text{Death}, & \text{if } \gamma < 0.25 
\end{cases}
\] (26)

The population size will remain at the same level and will not decrease to 50% of the initial one. The reproduced individual, \((Y_{ij}^{(rep)})\), is obtained by (27), which takes average of best solution at \(i_{th}\), \((Y_{ij}^{(best)})\), and randomly selected individual, \((Y_{ij}^{(p)})\), form top 10% population excluding the best one, to replace dead individuals so that population size does not change.

\[
(Y_{ij}^{(rep)}) = \frac{(Y_{ij}^{(best)}) + (Y_{ij}^{(p)})}{2} \] (27)

V. SYSTEM DESCRIPTION

A residential electricity consumer having 12 household appliances is considered with integration of ESS, and PV generation for validation of the proposed methodology. The user-defined operational preferences of home appliances are provided in Table 1.

| Appliance category | Appliance     | Power rating (kW) | Start time (h) | End time (h) | Operation time (h) |
|--------------------|---------------|-------------------|----------------|--------------|-------------------|
| BLAs               | Refrigerator  | 0.3               | 1              | 24           | 24                |
|                    | Interior lighting | 0.84             | 18             | 24           | 6                 |
| UDAs               | Washing machine | 1.5              | 9              | 12           | 2                 |
|                    | Spin dryer    | 2.5              | 13             | 18           | 1                 |
|                    | Dish washer  | 1.5              | 9              | 17           | 2                 |
| IDAs               | Desktop       | 0.3              | 18             | 24           | 3                 |
|                    | Laptop        | 0.1              | 18             | 24           | 2                 |
|                    | Microwave     | 1.7              | 6              | 10           | 1                 |
|                    | Vacuum cleaner | 1.2              | 9              | 17           | 1                 |
|                    | Cooker hub   | 3                | 6              | 10           | 1                 |
|                    | Cooker oven  | 5                | 18             | 20           | 1                 |
|                    | Electrical car | 3.5             | 18             | 8            | 3                 |

For the case study, the solar irradiance data has been taken from from [38] and data variability is modeled by beta-distribution model to produce patterns of daily solar irradiance as explained in [39]. The parameters for home energy sources are provided in Table 2. In this study, real-time tariff scheme is considered for purchasing the electrical energy, which is provided in Figure 2 [39]. For home energy export, it is assumed that energy can be exported to the main grid at half price of real-time import tariff. In this work, three different cases are analyzed in the presence of grid supply, the ESS (battery), and PV generation as given in Table 3. These cases are used to analyze the impact of optimal DRAs scheduling on ECC by considering the integration and absence PV system and ESS.

VI. RESULTS

In this section, simulation results and discussions are presented to analyze the HEMS performance with DRAs scheduling with PV system, ESS, and energy transaction with main grid. The HEMS problem is solved using GWO, GA, and proposed PBO considering three case studies presented in Table 3. The developed DRAs scheduling problem is optimally solved and evaluated 50 times for each considered algorithm. All the results, presented in following subsections, represent the average value of these 50 runs for each algorithm. In all the considered cases, the performance of the proposed PBO results is compared with other metaheuristic algorithms to prove its effectiveness in obtaining optimal DRAs scheduling.

A. CASE A: HEMS WITH UTILITY ONLY

In this case, a residential home is considered with no PV and ESS installation. Therefore, such electricity users can only meet their energy demand by purchasing electricity from the main grid and have no provision of selling energy back to the main grid.

1) ELECTRICITY COST

In the unscheduled case, the DRAs adjust their operation according to consumer preferences by conventionality purchasing electricity from the main grid at the provided energy buying prices. In this case, the energy demand reaches its

| Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|
| \(P_{pv,n}\) | 5 kW  | \(\eta_{inv}\) | 0.95  |
| \(P_g\) | 10 kW | \(C_b\) | 4 kWh |
| \(P_{b,\max}\) | 3 kW  | \(P_{d,\max}\) | 3 kW  |
| \(\eta^c\) | 80%  | \(\eta^d\) | 80%  |
| \(SOC_{\max}\) | 90%  | \(SOC_{\min}\) | 30%  |
peak from 10:00 to 11:00 as shown in Figure 3. The real-time price is also maximum during this period. Hence, the total ECC is high without using optimal DRAs scheduling. On the contrary, in the scheduled case A, the considered metaheuristics algorithms GWO, GA, and the proposed PBO optimally schedule the DRAs under real-time price scheme. The total ECC is 474.06, 462.68, and 441.46 cents, for GWO, GA, and the proposed PBO, respectively. Hence the total ECC has been reduced by 10.25%, 12.4%, and 16.41% in case of GWO, GA, and the proposed PBO, respectively, which is also shown in Table 4. The total ECC for the unscheduled and case A with GWO, GA, and the proposed PBO algorithms is provided in Figure 4. The total ECC is minimum in case of the proposed PBO algorithm.

2) PAR
In the proposed HEMS architecture, EMC optimally schedules the DRAs to minimize the peak demand such that PAR is reduced in comparison with unscheduled case. The PAR for the unscheduled case, GWO, GA, and the proposed PBO was 4.44, 3.77, 3.63, and 3.11, respectively. The PAR comparisons of GWO, GA, and the proposed PBO with unscheduled case are presented in Table 4. The GWO, GA and the proposed PBO have reduced PAR by 15.09%, 18.24%, and 29.96%, respectively, as compared to the unscheduled case.

Figure 5 shows that the PAR achieves minimum value in case of proposed PBO algorithm.

B. CASE B: HEMS WITH AN ESS
In case B, the residential customer have their own ESSs installed along with main grid to meet their energy demands without involving PV system. The hourly electricity transactions in this case are shown in Figure 6. The residential consumers buy energy from main grid for storage in their ESSs during low energy buying price periods. During high energy buying price hours, the ESS discharges to provide energy to consumer load such that no or minimum electricity can be bought from main grid to meet energy at that time. When ESS have more energy stored after meeting the total load demand, the consumer neither buys nor sells energy to main grid.

1) ELECTRICITY COST
After finding the optimum scheduling of home appliances in presence of ESS through GWO, GA, and the proposed PBO algorithm with the consideration of real-time tariff signal, the ECC were 422.39, 410.08, and 398.34 cents, respectively. Hence, the optimum ECC through GWO, GA, and the proposed PBO is reduced by 20.01%, 22.36%, and 24.58%, respectively, with the respect to unscheduled case, as
provided in Table 4. The total ECC for the unscheduled case and case B with GWO, GA, and the proposed PBO algorithms in the presence of real-time tariff scheme is shown in Figure 7 to validate the better performance of proposed PBO.

2) PAR
With ESS integration in DRAs scheduling problem, PAR has considerably reduced. The effective peak demand has been decreased due to energy availability from ESS stored electric energy to meet partially peak demand before buying remaining energy demand from main grid. The PAR is 4.44 in unscheduled case, which has been decreased to 3.41, 3.58, and 3.05 with optimal DRAs scheduling using GWO, GA, and PBO, respectively as presented in Figure 8. After the optimal DRAs scheduling through GWO, GA, and the proposed PBO algorithms, the comparative reductions in PAR are 23.19%, 19.37%, and 31.31%, respectively, with respect to unscheduled case.

C. CASE C: HEMS WITH ESS AND PV
In this case, the residential customers have installed both PV system and ESS. They meet their energy demand by using electric energy from the ESS, PV generation system, and main grid. At each time instant, when combined PV and ESS energy is not enough to meet the required energy demand, the deficit energy is purchased from main grid at real-time energy prices. On the contrary, when excess energy is available, it is exported to main grid at half of the buying electricity cost. At time instants, 7, 8, and 11 to 18, the surplus energy is available and it is exported to the main grid. Therefore, the overall ECC reduces, and the residential customer gets the advantages of net metering. The per-hour electricity transaction with main grid for this case is presented in Figure 9.

1) ELECTRICITY COST
The GWO, GA, and the proposed PBO technique optimally schedule the DRAs with the integration of PV, ESS, and utility and use of real-time energy prices. These algorithms achieve optimal ECC values of 322.65, 315.6, and 284.4 cents, respectively. Compared with the unscheduled case, the optimum scheduling purchasing cost through GWO, GA, and the proposed PBO is decreased by 38.92%, 4.25%, and 46.15%, respectively, as shown in Table 4. The total ECCs for the unscheduled and scheduled cases using real-time energy prices are shown in Figures 10.

| Case | method | ECC (US cents) | ECC reduction (%) | PAR | PAR reduction (%) |
|------|--------|----------------|-------------------|-----|-------------------|
| Unscheduled | - | 528.18 | - | 4.44 | - |
| A | GWO | 474.06 | 10.25 | 3.77 | 15.09 |
| | GA | 462.68 | 12.40 | 3.63 | 18.24 |
| | Proposed PBO | 439.46 | 16.41 | 3.11 | 29.96 |
| B | GWO | 422.39 | 20.01 | 3.41 | 23.19 |
| | GA | 410.08 | 22.36 | 3.58 | 19.37 |
| | Proposed PBO | 398.34 | 24.58 | 3.05 | 31.31 |
| C | GWO | 322.65 | 38.92 | 3.37 | 24.10 |
| | GA | 315.60 | 40.25 | 3.59 | 19.14 |
| | Proposed PBO | 284.40 | 46.15 | 2.73 | 38.51 |

2) PAR
When both PV and ESS are included in the proposed model, PAR has been greatly decreased. The PAR for the unscheduled case, GA, GWO, and the proposed PBO is found to
be 4.44, 3.37, 3.59, and 2.73, respectively. The GWO, GA, and the proposed PBO reduced the PAR as compared to the unscheduled case by 24.1%, 19.14%, and 38.51%, respectively, as shown in Table 4. Figure 11 represents the PAR of the unscheduled case and case C with GWO, GA, and the proposed PBO algorithms, which shows that PAR achieves optimum least value in case of proposed PBO algorithm.

D. EXECUTION TIME COMPARISON

To equate the executional time of the GA, GWO, and PBO, each of them was run 50 times to obtain the solution of the scheduling problem. Different indicators of execution time for different cases using the real-time tariff scheme are shown in Table 5. For all cases, when we compare the execution time of the proposed PBO technique with the GA and GWO for 50 runs to achieve the optimal solution, it can be perceived that the proposed PBO algorithm required the lowest average execution time as compared to the GA and GWO. In considered case study, with the addition of PV and ESS the complexity of the case study augmented. Due to this, the simulation time will be increased regardless of the algorithm applied. From Table 5, it is also obvious that the proposed PBO algorithm was the more time-efficient algorithm as compared to other algorithms. The standard deviation can be a good indicator to assess the performance of an optimization algorithm for its consistent optimal solutions.

In terms of execution time, the standard deviation was calculated along with its maximum and minimum values, and the results are presented in Table 5. It can be noted that the standard deviation in execution time of the proposed PBO was better for all cases in comparison with the GA and GWO, which validates the performance of the proposed technique.

VII. CONCLUSION

In this paper, a grid-connected home energy management system model was proposed using demand responsive appliances, photovoltaic, and energy storage systems. A new optimization technique called polar bear optimization algorithm was applied to optimally schedule the home demand responsive appliances with the objectives of minimizing electricity consumption cost and reducing PAR under real-time pricing program. To evaluate the performance and effectiveness of the proposed technique, three scenarios were considered, and the obtained results were compared with grey wolf optimization, genetic algorithm, and the unscheduled methods.

It has been observed from simulation results that in case A, the electricity cost is reduced by 10.25%, 12.40%, and 16.41% percent using GWO, GA, and the proposed PBO, respectively and the PAR is minimized by 15.05%, 18.24%, and 29.96%, respectively. In case B, after the integration of ESS the electricity cost is decreased by 20.01%, 22.36%, and 24.58% and the PAR is reduced by 23.19%, 19.37%, and 31.31% using GWO, GA, and the proposed PBO, respectively. In case C, after the integration of both ESS and PV the electricity cost is minimized by 38.92%, 40.25%, and 46.15% using GWO, GA, and the proposed PBO, respectively.

The results of the execution time demonstrated that the convergence rate of the proposed PBO for the scheduling of appliances was comparatively fast, and therefore, this technique can be a better choice in real-time applications in smart homes for appliances scheduling. The proposed algorithm for the optimal appliance scheduling strategy can be applied to actual data when and where they are provided. It not only reduced the energy cost, but also increased the stability and reliability of the grid. In addition, the contribution of scheduling results for several HEMSs can be important for...
an aggregator to manage its resources for a cost-effective and reliable operation of a microgrid.

This work focused on residential loads; however, an increase in the number of appliances and the incorporation of loads of other energy sectors, i.e., industrial and commercial, is planned for future work.

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