IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received July 19, 2020, accepted July 25, 2020, date of publication July 29, 2020, date of current version August 10, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3012735

Heuristic-Based Programable Controller for Efficient Energy Management Under Renewable Energy Sources and Energy Storage System in Smart Grid

ADIL IMRAN[1], GHULAM HAFEEZ[1,2], IMRAN KHAN[1], (Senior Member, IEEE), MUHAMMAD USMAN[3], (Senior Member, IEEE), ZEESHAN SHAFIQ[1], ABDUL BASEER QAZI[4], (Member, IEEE), AZFAR KHALID[5], AND KLAUS-DIETER THOBEN[6,7]

[1]Department of Electrical Engineering, University of Engineering and Technology, Mardan, Mardan 23200, Pakistan
[2]Department of Electrical and Computer Engineering, COMSATS University Islamabad, Islamabad 44000, Pakistan
[3]Department of Computer Software Engineering, University of Engineering and Technology, Mardan, Mardan 23200, Pakistan
[4]Department of Software Engineering, Bahria University, Islamabad 44000, Pakistan
[5]Department of Engineering, School of Science and Technology, Nottingham Trent University, Nottingham NG11 8NS, U.K.
[6]University of Bremen, 28359 Bremen, Germany
[7]BIBA—Bremer Institut für Produktion und Logistik GmbH, 28359 Bremen, Germany

Corresponding author: Azfar Khalid (azfar.khalid@ntu.ac.uk)

This work was supported by the National Natural Science Foundation of China under Grant 61803115.

ABSTRACT An operative and versatile household energy management system is proposed to develop and implement demand response (DR) projects. These are under the hybrid generation of the energy storage system (ESS), photovoltaic (PV), and electric vehicles (EVs) in the smart grid (SG). Existing household energy management systems cannot offer its users a choice to ensure user comfort (UC) and not provide a sustainable solution in terms of reduced carbon emission. To tackle these problems, this research work proposes a heuristic-based programmable energy management controller (HPEMC) to manage the energy consumption in residential buildings to minimize electricity bills, reduce carbon emissions, maximize UC and reduce the peak-to-average ratio (PAR). We used our proposed hybrid genetic particle swarm optimization (HGPO) algorithm and existing algorithms like a genetic algorithm (GA), binary particle swarm optimization algorithm (BPSO), ant colony optimization (ACO), wind-driven optimization algorithm (WDO), bacterial foraging algorithm (BFA) to schedule smart appliances optimally to attain our desired objectives. In the proposed model, consumers use solar panels to produce their energy from microgrids. We also perform MATLAB simulations to validate our proposed HGPO-HPEMC (HHPEMC), and results confirm the efficiency and productivity of our proposed HPEMC based strategy. The proposed algorithm reduced the electricity cost by 25.55%, PAR by 36.98%, and carbon emission by 24.02% as compared to the case of without scheduling.

INDEX TERMS Smart grid, energy management, efficient energy utilization, energy storage system, heuristic algorithms, energy management controller, renewable energy sources, carbon emissions.

NOMENCLATURE

μ	Inertia factor
F_c	Coriolis force
Ω	Rotation of earth
α	Friction coefficient
ρ	Air density
Δ	Pressure gradient
δv	Finite volume of the air
g	Acceleration of gravity
z	Ant
x	Set
v	Smart home
T	Time interval
M	Shiftable appliances
N	Non-shiftable appliances

The associate editor coordinating the review of this manuscript and approving it for publication was Xiaofeng Yang.

t	Time slot
γ	Electricity emissions factor
η	price per kwh
m	Months in a year
P^{pv}	Hourly produced energy by solar panel
η^{pv}	Efficiency of solar panel
A^{pv}	Area of solar panel
$Irr(t)$	solar irradiance
$Temp(t)$	Outside temperature
$ES_{\min}$	Minimum level of battery
$ES_{\max}$	Maximum level of battery
η^{ESS}	Efficiency of battery
v_j^t	current Velocity
v_i^{t+1}	Velocity of particle
k	Random number
z_1	Local pull
z_2	Global pull
$X_{lbest,i}$	Local position
$X_{gbest,i}$	Global position
F_G	Gravitational force
T_{xy}	Pheromone level
E_P^c	Electricity bill of shiftable appliances
E_P^d	Electricity bill of non-shiftable appliances
$X^c_{m\in M}(t)$	On/off state of shiftable appliances
$X^d_{n\in N}(t)$	On/off state of non-shiftable appliances
P^{pv}	Hourly produced energy by solar panel
DR	Demand response
MIQP	Mixed integer quadratic programming
EUCs	Electric utility companies
BILP	Binary integral linear programming
EVs	Electric vehicles
CEAC	Certainty equivalent and adaptive control
RTP	Real time pricing
MOPSO	Multiple objective particle swarm optimization
PAR	Peak to average ratio
GA	Genetic algorithm
BPSO	Binary particle swarm optimization algorithm
ACO	Ant colony optimization
WDO	Wind driven optimization
HGPO	Hybrid genetic particle swarm optimization
ESS	Energy storage system
EMC	Energy management controller
HAN	Home area network
EDE	Enhanced differential evolution
SRDSM	Scalable robust demand side load management
HEM	Home energy management
DEM	Dynamic energy management
MILP	Mixed integration linear programming
GA	Genetic algorithm
ACO	Ant colony optimization
HGPO	Hybrid genetic particle swarm optimization
PAR	Peak to average ration
UC	User comfort
BFA	Bacterial foraging algorithm
RES	Renewable energy sources
SM	Smart meter
DG	Distributed generation
DSM	demand-side managemen
PV	Photovoltaic
IBR	incentive based regulation
TOU	Time of use
HPEMC	Heuristic-based programmable energy management controller
GWDO	Genetic wind driven optimization
DOD	Depth of discharge
SE	Stored energy
FA-HELF	Fast and accurate hybrid electrical energy forecasting

I. INTRODUCTION

Energy demand is increasing rapidly around the globe with population growth and economic development. Most of the traditional power generating plants run on fossil fuels and generate 64.5% of electricity worldwide [1]. These power plants have a larger share in carbon emissions, where approximately 40% carbon is emitted by the generation sector, and the transport sector [2] produces 24%. Furthermore, to reach the drastically increasing energy demand with lower carbon emissions, researchers have proposed new methods of energy generation using renewable energy sources (RESs). To effectively utilize these sources, we have to transform existing power grids into smart grids (SG). In [2], a SG is defined as "it is an electricity supply network that can smartly incorporate the actions of all users linked to it like generators, consumers and prosumers (all those do both generation and consumption)." SGs works with different kinds of devices such as smart meters (SMs), smart appliances, RESs, and batteries. The main purpose is to control power generation, power transmission, and power distribution through modernistic techniques. In SGs, we have two-way communication between electric utility companies (EUCs) and the end-user. Moreover, two-way communication in SG keeps the consumers well informed regarding their electricity bills and allows the users to observe and examine the real-time data of energy usage. The SG builds the integration of distributed generation (DG) and RESs, viable. It involves the commercial and residential users participating in demand response (DR) and demand-side management (DSM) activities. The main goal of DSM is to motivate the users to shift the time of energy consumption to off-peak hours or use minimum energy during peak hours [4]. It is completely daring to ask the users to schedule their use of appliances by limiting their comfort level. Consequently, the home energy management system (HEMS) is needed, which handles household load scheduling. The highlights of our work are as follows:

1) Hybrid generation system of the energy storage system (ESS), photovoltaic (PV), electric vehicles (EVs), and electric utility companies (EUCs) have been proposed to solve energy management problems.

2) The PV, ESS, EVs, and household load is made controllable so that energy management is possible.
3) In addition to cost, PAR, UC objectives, carbon emission is formulated and investigated to solve energy management problem by power usage scheduling of smart appliances under hybrid generation to improve sustainability.
4) Four performance metrics, electricity cost, PAR, UC, and carbon emission are mathematically modeled simultaneously.
5) An HGPO algorithm is introduced, which is a combination of BPSO and GA to perform optimal energy management.
6) A heuristic optimization algorithm HGPO-based energy management controller (HPEMC) is proposed for optimal energy management under hybrid generation and price-based DR programs.
7) A practical optimization model for energy management is formulated for power usage scheduling under hybrid generation utilizing AMI and price-based DR programs. This is real-time pricing (RTP) of the SG.
8) Objective function and constraints are constructed to manage power usage of smart home appliances under hybrid generation to minimize the cost of electricity, alleviate PAR, minimize carbon emission, and maximize UC.
9) Simulation results prove that proposed HPEMC-based technique has outclassed existing strategies in terms of electricity bill, PAR, UC, and carbon emission.

We organized the remainder of the paper as follows: section II explains the related work, section III briefly explains the proposed algorithms, section IV describes the proposed system model and in section V, we have discussed the simulation results. We have finally concluded the work in section VI.

II. RELATED WORK

In the last decade, numerous DSM techniques have been presented. All of them have common objectives of minimizing the cost, PAR, and carbon emissions. Previously, many techniques have been used to solve the appliances scheduling problem which is tabulated in Table 1.

In [5], the authors proposed GA and compared its results with WDO. The results showed a 29% reduction in the EC and a 36.2% reduction in the PAR. The authors used HEDS in which they discussed the operating power of different appliances, however, they did not use any of the RESs in their work. They only scheduled the operating time of the appliances. The authors in [6] presented multiple integration linear programming (MILP) techniques for scheduling the appliances. Their objectives were minimization of cost and linearization of the load curve. They used RESs and EVs in their work, however, UC has not been considered. In [7], the authors proposed GA, WDO, BPSO, and BFA techniques to minimize cost and PAR. They compared their results and concluded that the HGPO algorithm outperforms the other algorithms in reducing cost and PAR. HGPO algorithm reduces cost by 25.12% and PAR by 24.88%. Although, the results are slightly better, the appliance scheduling time is slow. The authors in [8], have proposed certainty equivalent and adaptive control (CEAC) technique for charging the EVs. Their objectives were voltage regulation and adoption of RE. They used wind energy and the electric grid for the charging of the EVs. However, they didn't discuss the discharging of EVs back to the electric grid. In [9], authors presented a binary integer linear programming (BILP) technique. They achieved their objectives by reducing cost by 35% and also compared their results with the MILP algorithm. However, there was a lack of application of RESs in their work, which might improve results further. The authors in [10], have proposed a dynamic energy management algorithm (DEM). Their objectives were demand-side load management and voltage fluctuation of RESs. They used PV, ESS, UC, and grid in their system. Although their results were impressive, the system is costly, and they didn't consider UC either. The authors in [11] have proposed the WDO approach with the objective of minimizing cost. They used boiler and solar thermal storage in their system to reduce cost by 18.48%. However, their work is only limited to a small scale residential side. In [12], the authors proposed optimal power management for a nano-grid containing a small number of houses. They have used multiple objective optimization to schedule the shiftable appliances for minimizing the load curve, but, didn't consider UC. MILP is used in [13], and the objective has cost reduction while RESs with EVs was in use. They concluded that the total electricity cost in a vehicle to home (V2H) mode is 2.6% less than that of home to a vehicle (H2V). However, they didn't consider PAR and carbon emissions in their work. In [14], the authors proposed a two-stage home energy management (HEM) strategy equipped with RESs. The operational cost of homes was minimized in the one stage, while in the second stage, PF was improved. Also, an effective model was produced, and appropriate linearization techniques were applied to compensate for the non-linear nature of the produced model. The authors in [15] presented the game theory technique. Their objectives include cost-minimizing and load scheduling. They also proposed a smart pricing tariff, to encourage the users to minimize the energy cost. However, they did not consider UC in their work. In [16], authors proposed a close to real-time EMS for multiple houses of residential buildings. They also used a mixed-integer linear programming model to control the washing machine, dishwasher and the ESS in a smart building. The results prove that the proposed model can help minimize the building's energy by 9% and PAR by 18.78%. Although their results are encouraging, their work is only for small residential areas. In [17], the authors proposed a fuzzy logic controller to operate fuel cells efficiently and safely. The objective was to utilize RESs efficiently. As a result, the efficiency of wind increased by 2.5%, solar increased by 2%, while fuel cell (FC) decreased by 4% annually. The

TABLE 1. Related work.

Reference	Technique	Objectives	Research Gaps
[5]	GA	Cost reduction, PAR, UC	CO_2 emissions is not considered
[6]	MILP	Cost reduction, PAR	UC is ignored
[7]	GA, WDO, PSO, BFA	Cost reduction, PAR	UC is ignored
[8]	CEAC	Penetration of RESs	CO_2 is not considered
[9]	BILP	Cost reduction	PAR is not considered
[10]	DEM	PAR, voltage fluctuation	UC is not considered
[11]	WDO	Cost reduction	Inconvenient for users
[12]	Multiple Objective Optimization	Cost reduction	UC is not considered
[13]	MILP	Cost minimizing	PAR is not considered
[14]	HEM	Cost minimizing, PAR	CO_2 emissions is not considered
[15]	Game theory	PAR, cost reduction	Inconvenient for users
[16]	MILP	Cost reduction, PAR	CO_2 is not considered
[17]	Fuzzy logic	Cost reduction	Inconvenient for users
[18]	HEM	Cost reduction, PAR	CO_2 is not considered
[20]	Backtracking algorithm	Cost reduction, PAR	Inconvenient for users
[21]	GA	Cost reduction, PAR	Inconvenient for users
[22]	MILP	PAR	CO_2 is not considered
[23]	Stackelberg game theory	Cost minimizing	Inconvenient for users
[24]	MIQP	Cost reduction	CO_2 is not considered
[25]	Scalable robust demand side load management (SRDSM)	Reduction of cost	Not user comfortable
[26]	Multiple objective particle swarm optimization (MOPSO)	Carbon emissions, Cost reduction	UC is ignored
[27]	EMC	PAR reduction, Cost minimizing	Intermittency factor of wind is ignored
[28]	GA	Cost reduction, PAR reduction	Not applicable for commercial area
[29]	BILP	PAR reduction, Cost reduction	Only schedules the appliances
[30]	ACO	Cost minimizing, PAR reduction	CO2 emissions is not considered
[31]	Home area network (HAN)	Cost reduction, PAR reduction	CO_2 emissions is not considered
[32]	Enhanced differential evolution (EDE)	User comfort, cost reduction, PAR	UC is not considered

authors in [18] proposed a price-based HEM framework. The value of each appliance is determined in terms of the value of lost load (VOLL). VOLL is determined for residential users according to common time-varying tariffs like time of use (TOU) and incentive-based regulation (IBR). IBR leads to load balancing and PAR reduction. However, they didn't consider UC.

In [13], authors proposed BILP. They considered H2V mode and V2H mode. They inferred that the home with ESS does not buy electricity from the grid during peak hours. In the bidirectional case, V2H is 2.7% less than H2V mode. However, no uncertainty of load is discussed. Authors in [19] proposed a backtracking algorithm with Zigbee and smart sockets and proposed it for the BPSO algorithm. The objectives were the reduction in cost and PAR. As a result, they saved 20.55% energy on weekdays and 25% energy on weekends. While using the BPSO algorithm, they saved 21.7% on weekdays and 26.01% on weekends, however, they didn't consider UC. In [20], an energy management controller (EMC) to control the appliances and operate in low peak hours is proposed. They also made a combination of real-time pricing (RTP) and IBR to minimize both the cost and PAR. They used GA to schedule the shiftable appliances. However, the work is only valid for small residential areas. Authors in [21], presented MILP technique. They proposed the concept of prosumers. Prosumers mean the consumers who can produce and share an extra amount of energy. This will not only help the prosumers to earn money, but it can play an important role in PAR reduction. Authors in [22] proposed a fundamental and improved interaction strategy in which a grid and various buildings are produced using the Stackelberg game theory based on their recognized Nash equilibria, however, UC was ignored. The authors in [23] proposed mixed-integer quadratic programming (MIQP) to predict a control system established on the thermal building model and the building energy management system. The objective was to minimize cost, however, RESs were not utilized. Authors in [36] proposed a framework based on HEMC. They have also proposed a technique day-ahead grey wolf modified enhanced differential evolution algorithm (DA-GmEDE) to reduce the PAR and electricity bill. They have reduced cost and PAR by 23.9% and 43%, respectively. Authors in [37], proposed a fast and accurate hybrid electrical energy forecasting (FA-HELF) to forecast the electrical

TABLE 2. Parameters and values.

Algorithm Name	Parameters	Values
GA	Number of iterations	200
	Population size	200
	Pm	0.1
	Pc	0.9
	n	11
BPSO	Number of iterations	200
	Swarm size	200
	Vmax	4
	Vmin	-4
	Wi	2
	C1	0.4
	C2	2
	n	11
WDO	Number of iterations	200
	Population size	200
	dimMin	-5
	dimMax	5
	Vmin	-0.3
	Vmin	0.3
	RT	3
	n	11
	g	0.2
	α	0.4
BFO	Maximum generation	200
	Ne	24
	Nr	5
	Nc	5
	Np	30
	Ns	2
	Ci	0.01
	Ped	0.1
	θ	0.1
ACO	Max iteration	200
	Ant quantity	10
	Visibility intensity factor	6
	evaporation rate	5
	Pheromone intensity factor	2
	Trail decay factor	0.5
	Stopping criteria	Max iteration

energy consumption. In [38], authors have proposed GA, WDO, and BPSO algorithm to reduce electricity cost and PAR. As a result, they have minimized electricity bill and PAR by 22% and 29%, respectively. Authors in [39] proposed GA, WDO, and genetic WDO (GWDO) algorithm to avoid the load rise problem, electricity bill reduction, and PAR minimization. In [40], authors have proposed the Monti Carlo simulation to control carbon emission.

III. PROPOSED MODEL AND EXISTING MODELS

In this section, we will describe the methods that we have proposed in our work. We will also discuss the previous methods that have been done. We used GA, BPSO, WDO, BFA, HGPO, and ACO in our work because these algorithms adopts heuristic initialization, which leads to good solutions initially and then fills up the rest of the population with random solutions. Previously, many methods have been used for scheduling problems, which include LP, DP, MILP, etc. Nevertheless, these techniques face many difficulties in convergence, and they also cannot handle a huge number of appliances. BPSO, WDO, BFA, GA, HGPO, and ACO algorithms outperform the classical optimization techniques and give different methods to solve complex problems. The parameters and their values are given in Table 2.

A. GA

GA is influenced by the natural genetics procedure of the living organism [34]. GA offers alternative solutions in every single iteration. In GA, firstly a binary coded chromosome pattern is made, the chromosome pattern shows the On/Off condition of the appliances and the number of appliances are shown by the length of the chromosome.

After the initialization, a population (collection of possible solutions that displays the state of every appliance in a specified time slot) is produced. According to the objective function of the problem, the fitness function of every possible solution is checked. A new population is produced in each iteration by applying the genetic operations of crossover and mutation. Two binary chromosome strings are crossed over to form a new offspring, which would be different from its parents. In a crossover, we give the probability of crossover, that is how many times the crossover will take place. If the probability of crossover is 100%, then all offspring will be totally different from their parents. If the probability is 0%, then the whole offspring will be similar to their parents. 90-95% is the best crossover rate.

To produce some randomness in the offspring and to prevent the repetition of the population, we mutate the results. In the mutation process, several genes are changed in a chromosome from the primary state. The probability of mutation is very low. Once all the processes of crossover and mutation are performed, a new population is produced. Its fitness value is examined, and it is compared with the previous population. Figure 1 shows the flowchart of this algorithm.

B. BPSO ALGORITHM

PSO algorithm is another natural inspired technique for searching optimum solutions inside the search space. Mainly, it is present in a continuous domain. But, it can be improved to a discrete domain. BPSO is the discrete domain version of PSO. BPSO is mainly dependent on four factors: particle's own best position, initial velocity, global best position, and initial position amongst all the particles. In BPSO, a search space is produced, and a population randomly initialized and dispersed in the search space. Equation (1) in [33] is used to

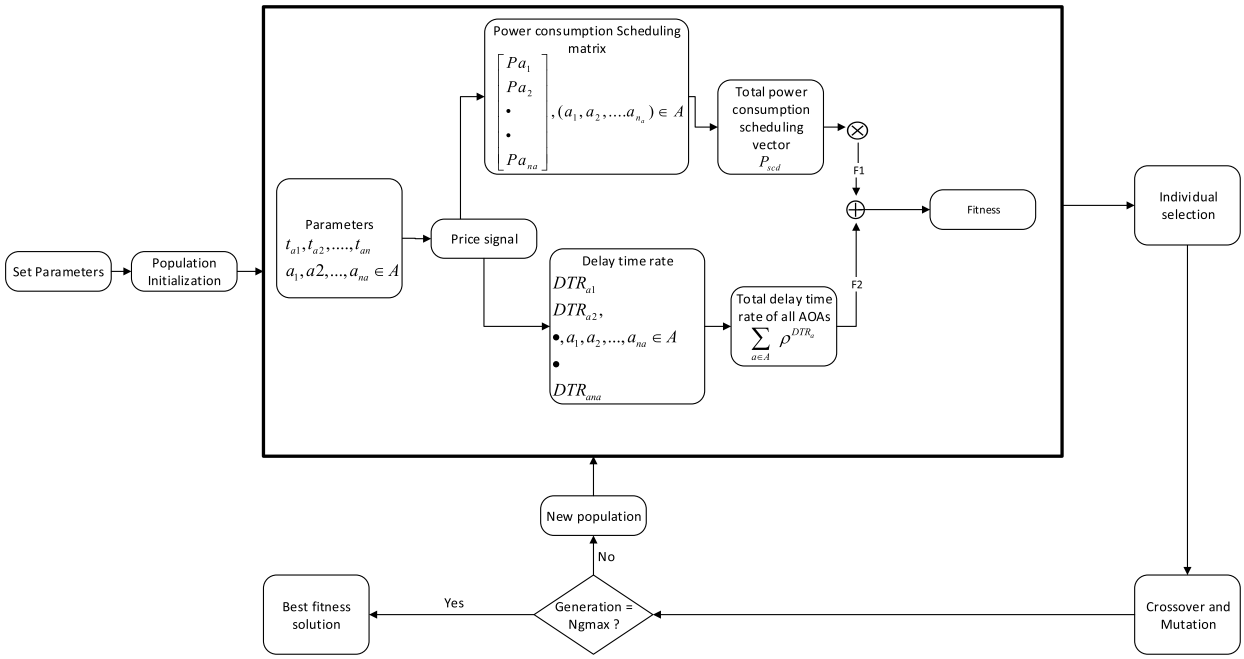

FIGURE 1. **Flow chart of GA.**

update the velocities of the particles in each iteration. Figure 2 shows the flowchart of this algorithm.

$$\sum_{t=1}^{24}\sum_{i=1}^{I}\sum_{t=1}^{24}\sum_{i=1}^{I} v_i^{t+1} = \sum_{t=1}^{24}\sum_{i=1}^{I} \mu v_j^t(j) + z_1 k_1 (X_{lbest,i}(j)) + z_2 k_2 (X_{gbest,i}(j) - x_i^t(j)) \quad (1)$$

where μ is the factor of inertia, v_j^t is current velocity. v_i^{t+1} is the velocity of particle. Random numbers are k_1 and k_2, while z_1 is local pull and z_2 is global pull. x_i^t is the particle's current position, $X_{lbest,i}$ is the local and $X_{gbest,i}$ is global best position. Equation (2) is used to map the velocities of particles between 0 and 1.

$$sim(v_i^{t+1}(j)) = \frac{1}{1+\exp(-v_i^{t+1}(j))} \quad (2)$$

C. WDO ALGORITHM

WDO is a heuristic optimization algorithm. WDO is based on the phenomenon of motion of air particles in the atmosphere. In this technique, an N-dimensional search space is produced in which infinite air particles move. WDO mainly comprises of four different forces to control air particles. These forces are gravitational, frictional, Coriolis, and pressure gradient. These forces have their functions as pressure gradient force shifts the particles in the forward direction, and the friction force resists this forward direction. Also, the gravitational force pulls the air particles towards the origin, while the Coriolis force's function is to deflect the air particles in the atmosphere. Equations (3), (4), (5), and (6) are used to calculate the pressure gradient force, Coriolis force, gravitational force, and friction force, respectively. All these forces can be mathematically written as [35]:

$$Fpg = -\Delta\rho\delta v \quad (3)$$
$$Fc = -2\Omega \times \mu \quad (4)$$
$$F_G = \rho\delta v \times g \quad (5)$$
$$F_F = -\rho\alpha\mu \quad (6)$$

where F_c represents the Coriolis force, and μ is the velocity factor of wind. The rotation of the earth is represented by Ω. F_F denotes the friction force while α is friction coefficient, Fpg is the pressure gradient force, δv is the finite volume of the air, the pressure gradient is denoted by Δ, F_G is the gravitational force, ρ is air density and g is the acceleration due to gravity.

WDO has n number of air particles, and random solutions are created from these particles. A new population is produced, after checking fitness function and updating velocities. After this, an optimal appliance scheduling pattern is obtained by comparing the fitness function of the old and new air particles. Figure 3 shows the flowchart of this algorithm.

D. ACO ALGORITHM

ACO is a meta-heuristic algorithm. Just like in real life, ants follow the shortest path for finding food and returning back to their nest. Ants use pheromone trail to detect their path again. In ACO, artificial ants and pheromone are produced to search for the shortest path in a graph. Pheromone is an evaporative element, so the ants will follow that path that has more pheromone. Just like other algorithms, ACO firstly builds an initial solution from a finite set of solution components. After this, the ant walks on the graph, where each vertex in

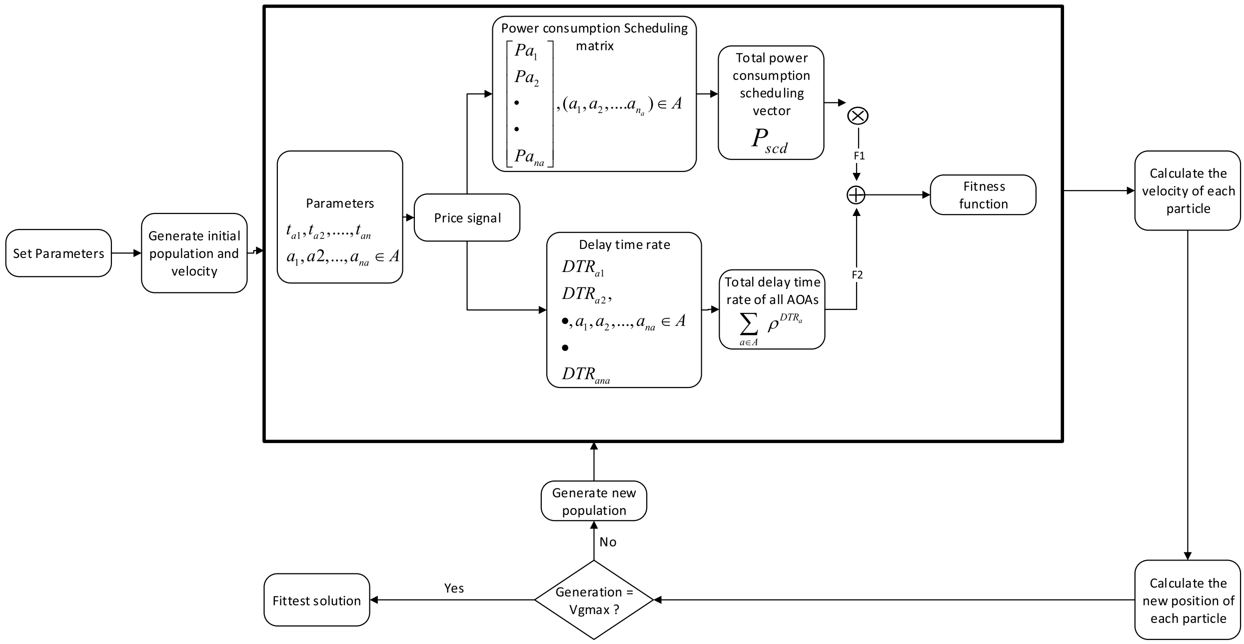

FIGURE 2. **Flowchart of BPSO algorithm.**

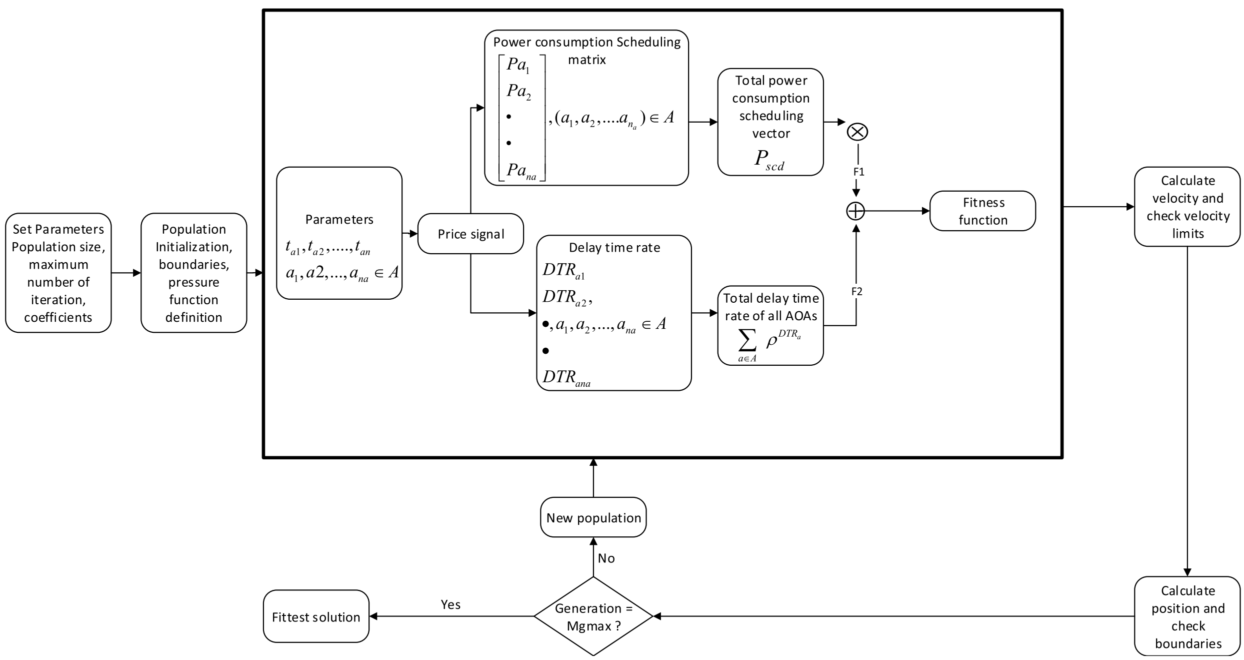

FIGURE 3. **Flowchart of WDO algorithm.**

the graph represents a solution component. The probability is defined as:

$$p_{xy}^{z} = \frac{T_{xy}^{\alpha} \eta_{xy}^{\beta}}{\sum k \in Az(x) T_{xk}^{\alpha} \eta_{xk}^{\beta}} \tag{7}$$

where z is an ant, state x computes a set $Az(x)$. The probability of the ant from moving from x to y is p_{xy}^{z}. T_{xy} is the pheromone level. Figure 4 shows the flowchart of this algorithm.

E. BFA

BFA is another nature-inspired algorithm. Since it has been useful in solving real-world problems, BFA has attracted the focus of many researchers. BFA algorithm has n number of nutrients (solution), the bacteria swim in search of best nutrients and to maximize their energy.

Similar to WDO, BFA also has four steps: reproduction, swimming, elimination-dispersal, and chemotaxis. BFA

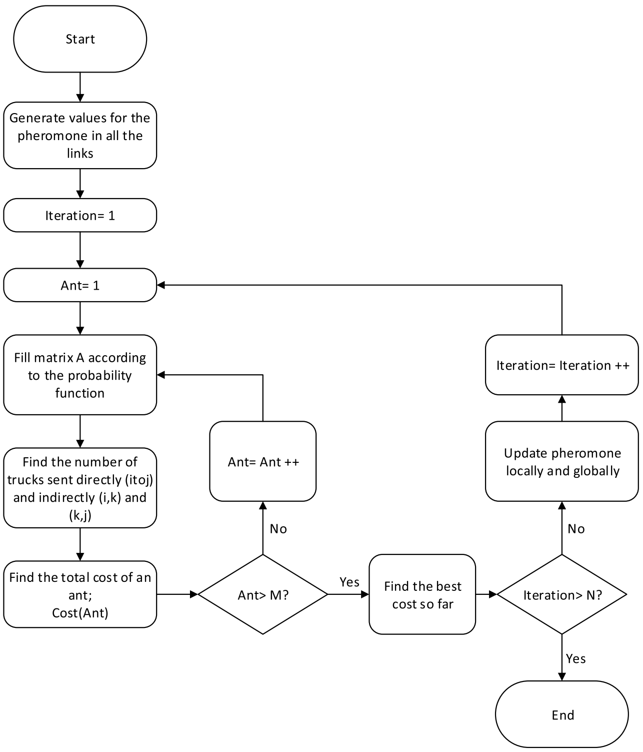

FIGURE 4. Flowchart of ACO algorithm.

starts its searching with parameters initialization under the chemotaxis step, after initialization of parameters, primary positions of appliances are examined, and then the new positions of bacteria (solution matrix) are calculated by the system. In the second step, for finding the current best condition of the appliances, the swimming loop is initialized. After this step is completed, iterations of the reproduction loop starts, in which only fittest solutions are taken to generate the new population. Lastly, the least fit solutions are eliminated, and new arbitrary samples are installed with a lower probability. This is an essential step because, in this step, the least fit solutions are removed, and the probability of repetition is minimized. Figure 5 shows the flowchart of this algorithm.

F. HGPO ALGORITHM

HGPO is our proposed algorithm. In this algorithm, we combine the product characteristics of GA and BPSO algorithms to efficiently minimize PAR, electricity cost, UC, and carbon emissions. We have chosen these two algorithms because GA reduces PAR efficiently, while BPSO can effectively reduce electricity cost. HGPO mainly has two stages where, in the first stage, the steps of BPSO are adopted. After that, the step of mutation and crossover of GA is employed to the current global best position X^{t-1}_{gbest}, found by BPSO. The application of mutation and crossover operated at the best positions provides good results than their application to the random population. Figure 6 shows the flowchart of this algorithm.

To evaluate the proposed and benchmark algorithms using test functions like Non-continuous Rastrigin's, Schaffer, and

Algorithm 1 HGPO Algorithm Based Energy Management Strategy in Smart Grid

```
Input: RTP DR program, length of operation time, power usage
pattern, temperature, solar irradiance, efficiency, appliances
pre-scheduling pattern, initialized ESS, and EVs.
Parameters initialization: maximum velocity, minimum velocity,
swarm size, local pull, global pull, initial momentum weight, final
momentum weight, PC, PM, cost, PAR, UC, and carbon emission.
for hours=1:24 do
    For initial position
    for h=1:swarm do
        for i=1:n do
            if rand>0.7 then
                X=1
            end
            else
                X=0
            end
        end
    end
    For initial velocity
    for v1=1:10 do
        for v2=1:6 do
            if timeslot=0 then
                H=0
            end
        end
    end
    Vbest1
    Pbest1
    begin
        Fitness evaluation
        Evaluate the Fitness function on first Position
        and Velocity
        Update the Velocity using Equation 1
        Update the Position using Equation 2
        Vbest2
        Pbest2
        Evaluate Fitness function on second best position and
        velocity
        Crossover [Pbest1 and Pbest2], Crossover result = cg
        Mutate[cg], Mutate result = Gbest
    end
    Returned Gbest
    begin
        Objectives determination
        for Utilized global best-returned results for UC calculation
        do
            UC 1.Power pattern=Gbest
            2.Calculate UC using Equation 23
        end
        for Utilized global best-returned results for cost
        calculation do
            Electricity cost calculation 1.Without PV and ESS,
            Load = power*Gbest
            2.With PV, LoadwithRESs=Load-Power enerated by
            PV
            3.With PV and ESS,
            LoadwithRESSESS=Load-Power
            generated by PV-Battery discharge
            4.Calculate Cost using Equation 20
        end
        for Utilized global best-returned results for carbon
        emission calculation do
            carbon emission 1.Without PV and ESS, take the
            average cost without PV and ESS
            2. With PV, take the average cost with PV
            3. With PV and ESS, take the average cost with PV
            and ESS
            4.Calculate carbon emission using Equation 22
        end
        for Utilized global best-returned results for PAR
        calculation do
            PAR 1.Withot PV and ESS, Load=Power*Gbest
            2.With PV, LdwithRESs=Load-Power generated by
            PV
            3.With PV and ESS, LdwithREES=Load-Power
            generated by PV-Battery discharge
            4.Calculate PAR using Equation 21
        end
    end
end
```

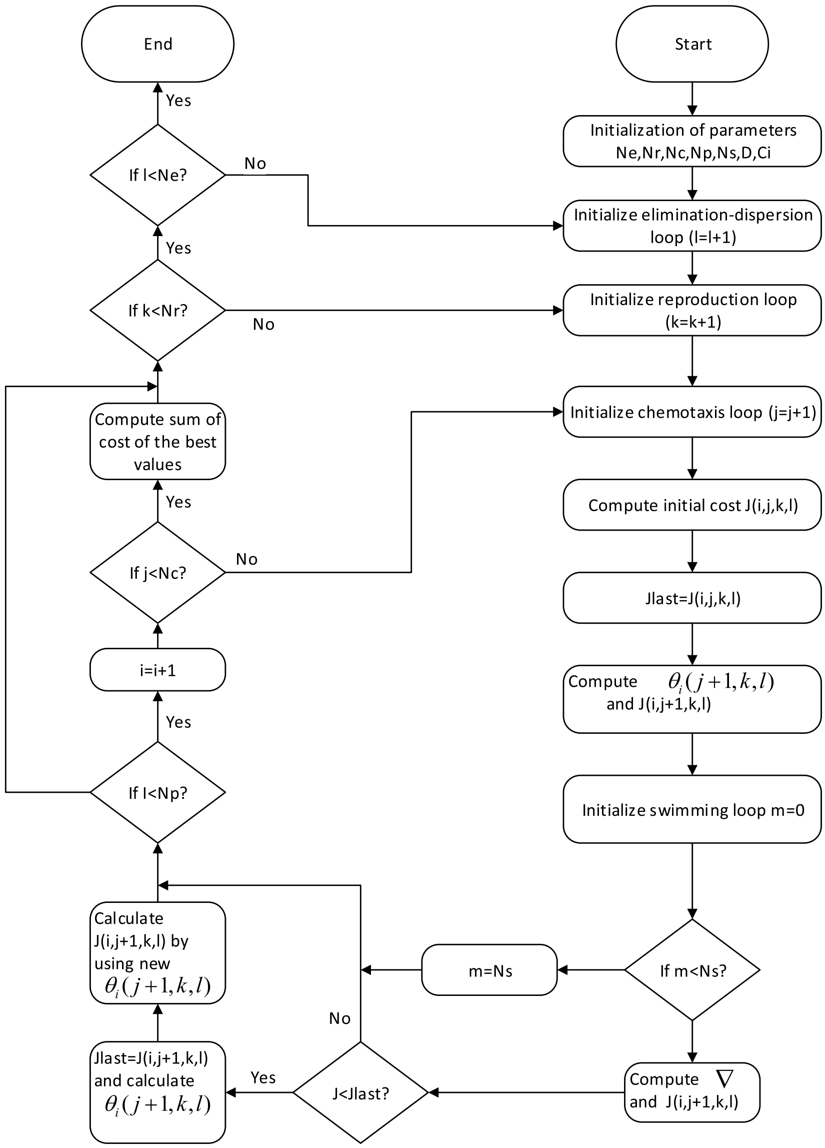

FIGURE 5. **Flowchart of BFA.**

Weierstrass are employed in simulations. These test functions are mathematically modelled as follows. The proposed algorithm outperforms the existing algorithm's fitness functions like Non-continuous Rastrigin's, Schaffer, and Weierstrass. The obtained results presented for test functions Schaffer, Weierstrasare, and Non-continuous Rastrigin's, shown in Figures 7, 8, and 9, respectively. Besides, the proposed and existing algorithms are compiled for 20 iterations mean, and standard deviation values are recorded using Schaffer, Weierstrass, and Non-continuous Rastrigin's benchmark functions. The results are listed in Table 3.

$$f(x) = 0.5 + \frac{Sin^2\left(\sqrt{x_1^2 + x_2^2}\right) - 0.5}{\left(1 + 0.001(x_1^2 + x_2^2)\right)^2} \tag{8}$$

$$\sum\nolimits_{i=1}^{D}\left(y_i^2 - 10cos(2\pi y_i) + 10\right)$$
$$y_i = \begin{cases} x_i & |x_i| < \frac{1}{2} \\ \frac{round(2x_i)}{2} & |x_i| \geq \frac{1}{2} \end{cases} \tag{9}$$

$$\sum\nolimits_{i=1}^{D}\left(\sum_{k=0}^{k_{\max}}\left[a^2 \cos\left(2\pi b^k\,(x_i + 0.5)\right)\right]\right) - D\sum_{k=0}^{k_{\max}}\left[a^k \cos\left(2\pi b^k 0.5\right)\right]$$
$$a = 0.5, \quad b = 3, \; k_{\max} = 20 \tag{10}$$

IV. SYSTEM MODEL

In this section, we presented the system model of our work. We considered smart homes, in which a smart home is

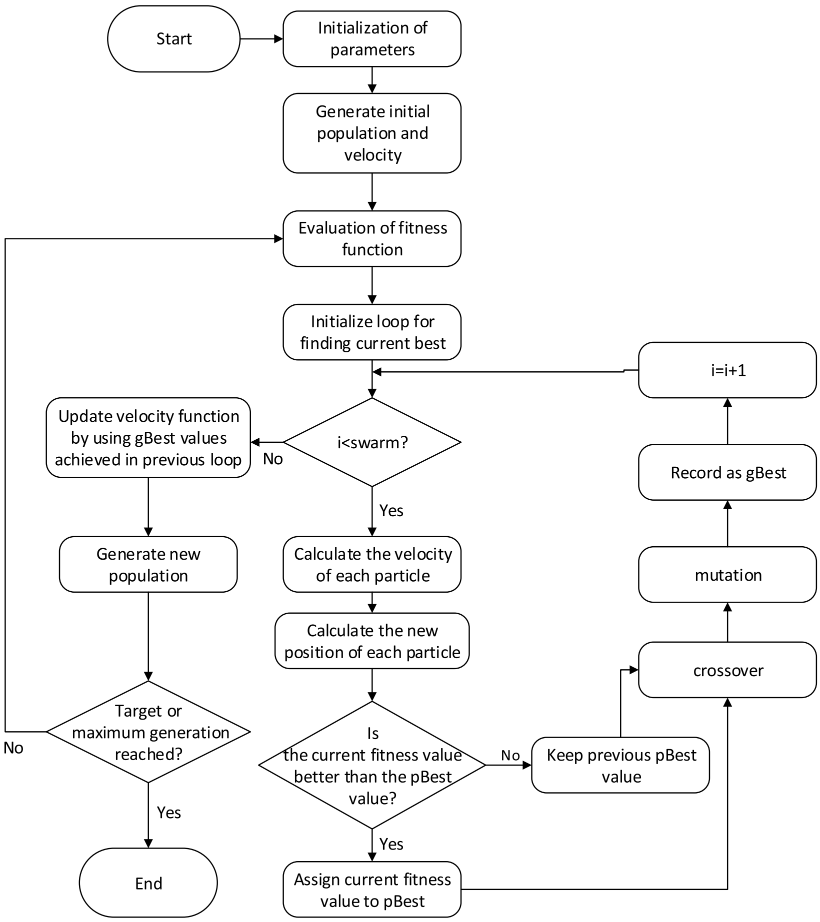

FIGURE 6. Flow Chart of our proposed HGPO algorithm.

TABLE 3. Results of the Proposed and Existing Algorithms for Benchmark Functions including Schaffer, Weierstrass, and Non-continuous Rastrigin's for 20 Iterations.

Optimization Techniques	Non-continuous Rastrigin Function	Schaffer Function	Weierstrass Function
BFOA Mean	0.165	5.844	0.028
STD.	0.734	3.536	0.006
GA Mean	0.945	10.844	0.632
STD.	1.674	9.032	1.865
BPSO Mean	0.000578	6.547	0.0096
STD.	0.000342	3.093	0.0082
GBPSO Mean	1.22E-11	8.02E-02	7.02E-18
STD.	2.76E-13	6.18E-02	1.04E-16
HBFPSO Mean	4.76E-17	1.49E-03	1.18E-24
STD	8.56E-16	7.35E-04	1.87E-23

denoted by v, which has different smart appliances. In the electric utility companies (EUCs) section, we consider a smart grid and a solar panel. In addition, for intelligent appliances, we installed an EMC which will schedule the appliances according to the pricing signal and electricity generation. We assume the duration of one day in this work, and the entire time interval is denoted by T. We have further divided one day into sub-intervals denoted by $t(1h)$. Figure 10 shows the system model of our work and figure 11 illustrates the working flow diagram of our model.

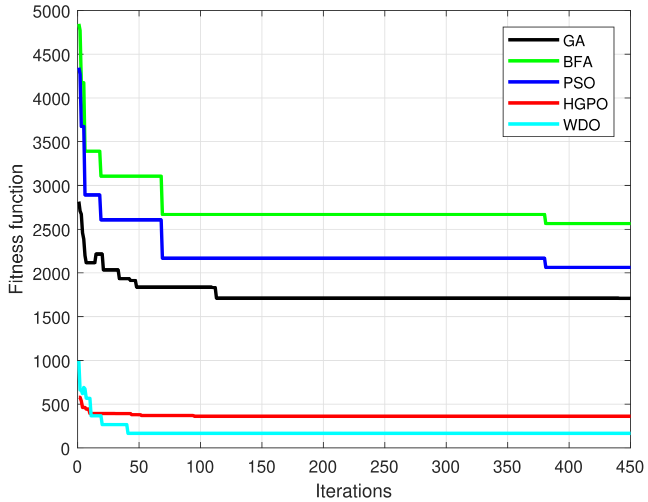

FIGURE 7. Performance evaluation of the proposed and existing algorithms using benchmark Schaffer test function.

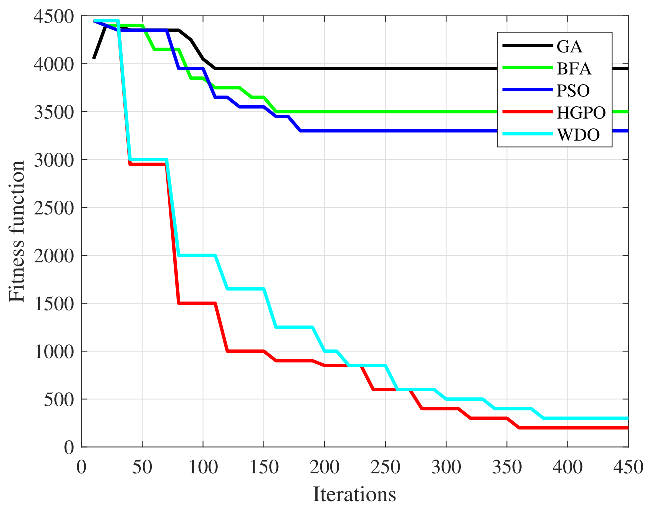

FIGURE 8. Performance evaluation of the proposed and existing algorithms using benchmark Weierstrass test function.

A. MATHEMATICAL FORMULATION

In this section, we have formulated our objective function, which is based on the reduction of electricity cost and PAR. The constraints are also presented in (12) to (16). We propose a MILP model for the scheduling of intelligent appliances. In this section, we will also formulate the RESs(PV) and also the ESS.

1) OBJECTIVE FUNCTION

Objective function is expressed as:

$$O = \min \sum_{t=1}^{T} (T^t_{sh} + T^t_{ns} - (E^t + ESS^t)) \times EP_t \tag{11}$$

constraints are:

$$T_{ns}(t) + T_{sh}(t) = (E(t) + ESS(t) + \phi(t)) \tag{12}$$

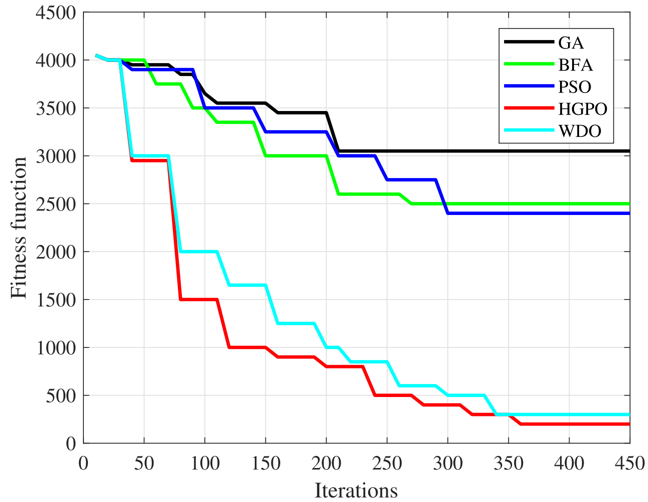

FIGURE 9. Performance evaluation of the proposed and existing algorithms using benchmark Non-continuous Rastrigin's test function.

$$\sum_{a=1}^{n} \eta = LOT(a) \tag{13}$$

$$\sum_{a=1}^{n} \alpha \leq \eta \leq \beta \tag{14}$$

$$\phi_t \leq KI \tag{15}$$

$$0 < ESS_{\min} < ESS_{\max}, \quad \forall t \varepsilon T, \tag{16}$$

The notations used in the objective function and all these constraints are detailed in the upcoming sections.

2) Electricity COST

To define the electricity pricing of a day, many electricity tariffs are available, like DAP, TOUP, PP, and RTP. In our model, we used RTP. In RTP, the electricity price changes every hour and remains constant for an hour. T E^c_P and E^d_P shows the daily electricity bill of shiftable and non-shiftable appliances, these are calculated in (17) and (18) respectively.

$$E^c_P = \sum_{t=1}^{24} \left(\sum_{M=1}^{m} (E^c_{m \in M}(t) \times X^c_{m \in M}(t) \times P^{RTP}(t)) \right) \tag{17}$$

$$E^d_P = \sum_{t=1}^{24} \left(\sum_{N=1}^{n} (E^d_{n \in N}(t) \times X^d_{n \in N}(t) \times P^{RTP}(t)) \right) \tag{18}$$

$$E^{tot}_P = E^c_P + E^d_P, \tag{19}$$

where $X^c_{m \in M}(t)$ and $X^d_{n \in N}(t)$ represents the on/off states of shiftable and non-shiftable appliances. M represent shiftable appliances, while N represent non-shiftable appliances in a particular time slot t. (19) is used to calculate the total electricity cost. Where E^{tot}_P denotes the total electricity cost. $E_P(t)$ at any time slot t represents the electricity bill after taking RESSs and ESS into consideration. It is calculated as;

$$E_P(t) = \left(E^c(t) + E^b(t) - E^{PV}(t) - SE(\tau) \right) \times P^{RTP}(t). \tag{20}$$

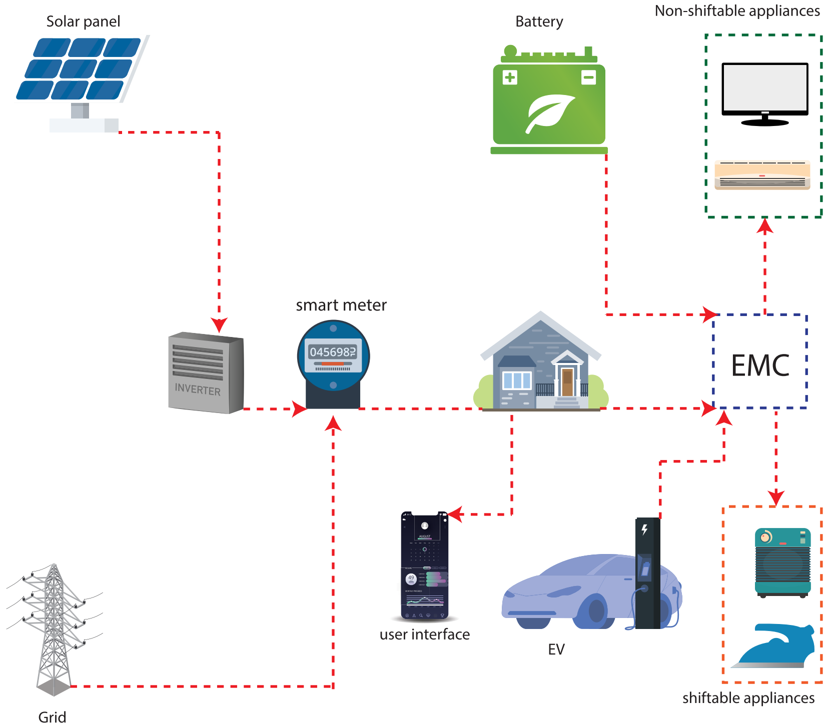

FIGURE 10. System model.

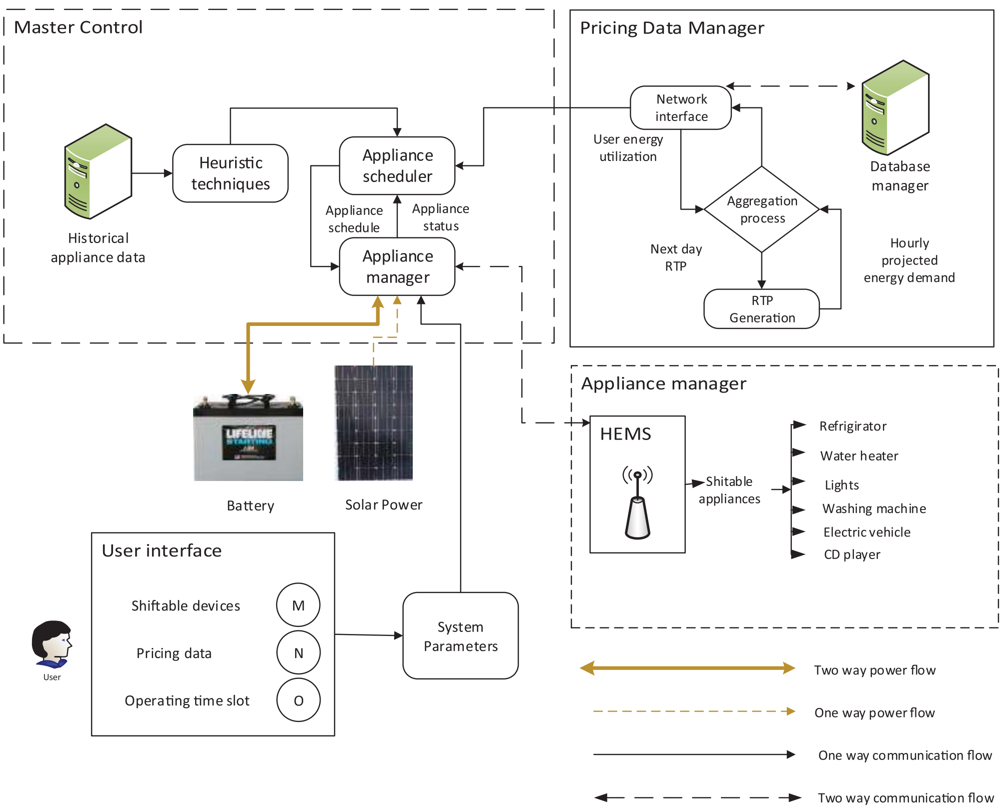

FIGURE 11. Working flow diagram.

where, τ represents the time slot between t_{20} to t_{24} having the highest electricity bill. The ESS is discharged because the PV is not available in those slots.

3) PAR

PAR is the ratio of peak load used in a time slot t and the average of total load used over the scheduling horizon, i.e., from $t = 1$ to $t = 24$. PAR tells us about the electricity consumption behavior of a user, and the consumers' PAR has a direct relation to the operation of EUCs peak plants. So, it is useful for both, EUCs and the consumers to minimize PAR so that demand balance and power supply can be maintained. For multiple users N, it can be calculated as:

$$PAR = \frac{\max(E_{tot}(t,m))}{\frac{1}{T}\sum_{m=1}^{N}\left(\sum_{t=1}^{T} E_{tot}(t,m)\right)} \tag{21}$$

4) CARBON EMISSION

(22) represents the carbon emission in pounds. Where $avgEP$ represents the average amount of electricity bill per month, while η shows the price per kwh. γ represents electricity emissions factor, while m represents months in a year. Electricity emissions factor is equal to 1.37 and price per kwh average is equal to 0.20 dollars.

$$CO_2 = \frac{avgEP}{\eta \times \gamma \times m} \tag{22}$$

5) USER COMFORT

The delay time of the appliance is calculated by (23). Where $undschd(t)$ represents the unscheduled time while $Schd(t)$ represents the scheduled time. Waiting time and electricity are both related to UC. We calculate UC in terms of waiting time.

$$Delay = \frac{\sum |Unschd(t) - Schd(t)|}{\sum (Schd(t))} \tag{23}$$

6) SOLAR PANEL

As we know, the solar panel produces its power from the sun, which is calculated as follows:

$$P^{pv}(t) = \eta^{pv} \times A^{pv} \times Irr(t) \times (1 - 0.005(Temp(t) - 25)), \tag{24}$$

where P^{pv} indicates the hourly produced energy by solar panel. The efficiency and area of the solar panel are represented as η^{pv} and A^{pv}, respectively. The terms $Irr(t)$ and $Temp(t)$ denotes the solar irradiance and outside temperature respectively, for time interval t.

B. STORAGE SYSTEM

This section will cover the energy storage system and their formulas, which are proposed in this work. In our work, we have two energy storage systems ESS.

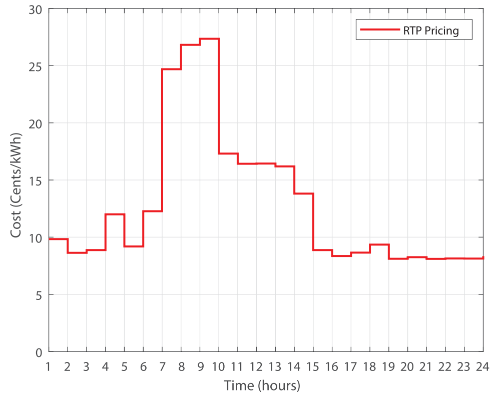

FIGURE 12. Real Time Pricing (RTP).

1) ESS

As we know that ESS has certain constraints, like charging, the minimum level is denoted by $ES_{\min}$ and the maximum level is denoted by $ES_{\max}$, respectively. Also, there are some limits for the discharging of ESS. The depth of discharge (DOD) is considered to be 90% in our work. The stored energy of ESS is expressed as:

$$SE(t) = SE(t-1) + k.\eta^{ESS}.ES^{ch}(t) - k.ES^{dis}(t)/\eta^{ESS}, \tag{25}$$

constraints are:

$$ES(t)^{ch} \leq ES_{\max}, \tag{26}$$
$$ES(t)^{ch} < ESS_{upl}, \tag{27}$$
$$ESS(t)^{dis} \geq ES_{\min}, \tag{28}$$

where SE denotes the energy stored (Ah) at time t, ES^{ch} shows the charging state and ES^{dis} shows the discharge state and η^{ESS} shows the efficiency of ESS, at time interval t and (26), (27) and (28) shows the constraints.

V. RESULTS AND DISCUSSION

In this section, we have presented the simulation results of the proposed HPEMC. In this system, the integration of RESs, ESS, and the performance of the HGPO algorithm, is evaluated in three scenarios. The first scenario is without PV and ESS, whereas, the second scenario is with PV only, and the third scenario is with PV and ESS. For our simulations, we used MATLAB.

To implement the proposed HPEMC, a user with 6 passive appliances and an ESS is considered as a source. To support the prosumers' load, we have taken the electric utility companies (EUCs) power supply available for 24 hours per day. The exogenic grid signals (RTP, forecasted temperature, solar irradiance) used in the proposed HPEMC are illustrated in figures 12, 13 and 14.

The power generation by PV system mainly depends on solar irradiance and ambient temperature. We have

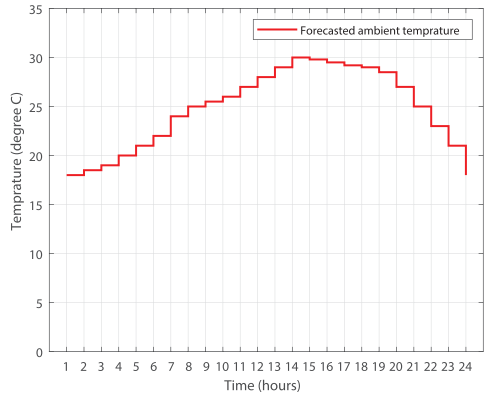

FIGURE 13. **Temperature.**

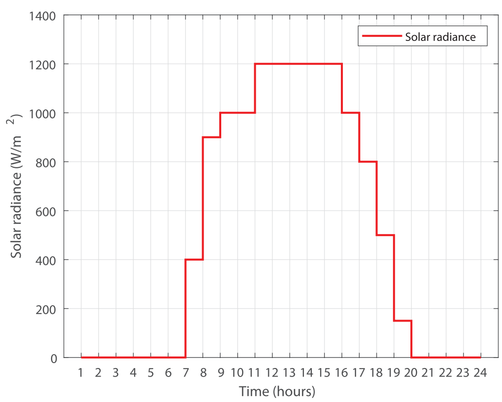

FIGURE 14. **Solar irradiance.**

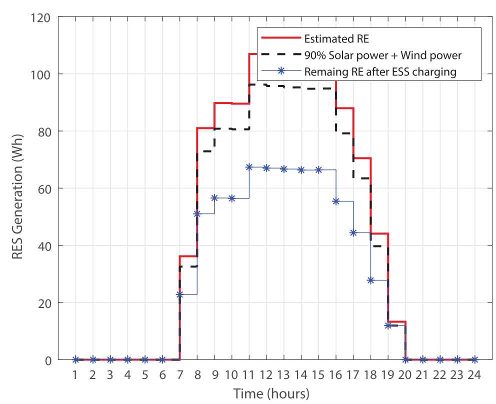

FIGURE 15. **Estimated RE.**

considered 90% of the total RE in any time slot of scheduling time. Also, for charging the ESS, 30% in each time slot is used of the 90% of RE. Figure 15 and 16 shows the estimated RE and charging level of ESS.

A. SCENARIO 1

In this scenario, we will not use PV and ESS; instead, we will just schedule the appliances by the scheduling algorithms. As a result, we will discuss electricity cost, carbon emission, and PAR.

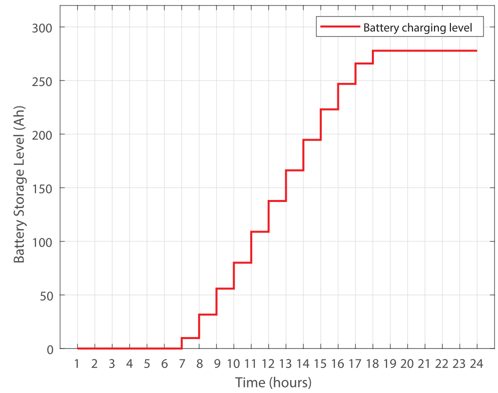

FIGURE 16. **Battery charging.**

TABLE 4. **Comparison of Scenario 1 Cost.**

Algorithm	Cost(cents)	Difference(cents)	Reduction(%)
Unscheduled	715	-	-
BPSO	680	15	4.89%
WDO	582	133	17.60%
BFA	590	125	16.34%
GA	681	34	4.75%
ACO	665	50	6.99%
HGPO	691	24	3.35%

1) **ELECTRICITY COST**

Figure 17 illustrates the electricity cost of scheduled and unscheduled load without ESS and PV. In BPSO, the maximum cost of electricity is 48 cents in the time slot 16. In WDO, the maximum cost of electricity is 46 cents in the time slot 23. While in the case of ACO, it is 38 cents in the time slot 22. In HGPO, it is 52 cents in the time slot 18, while in BFA, it is 44 cents in time slot 19. In GA based scheduled load, it is 57 cents in the time slot 7. The performance of the WDO algorithm in terms of electricity bill minimization is better than other heuristic algorithms.

The overall electricity cost in unscheduled load is 715 cents while using ACO, BPSO, WDO, GA, HGPO, and BFA are 665, 680, 582, 681, 691 and 590 cents, respectively. Overall, electricity cost shows that ACO, BPSO, GA, WDO, HGPO, and BFA reduce the electricity cost by 6.99%, 4.89%, 4.75%, 17.60%, 3.35%, and 16.34%, respectively. Nevertheless, where complete cost minimization is concerned, the WDO algorithm gives the best results when compared with other algorithms in this scenario. The comparison of cost in scenario one is shown in Table 4.

2) **PAR**

Figure 18 illustrates the PAR of the unscheduled and scheduled load. Results show that the proposed ACO algorithm reduces PAR by 30.11%. BPSO, BFA, WDO, GA, and HGPO also minimize the PAR by 12.5%, 14.55%, 8.33%, 20.83%, and 16.66% respectively. Although these algorithms reduce the PAR and avoid peak production, the GA and BFA algorithm mostly shifts the users load to off-peak hours and build

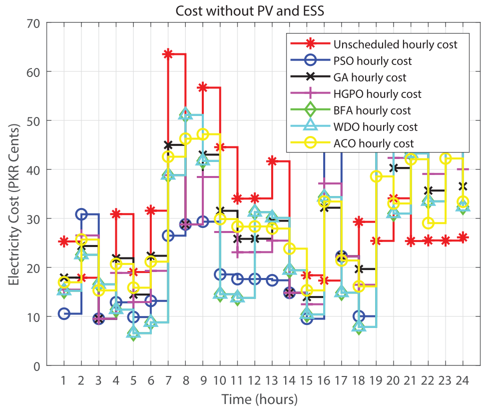

FIGURE 17. Cost reduction in scenario 1.

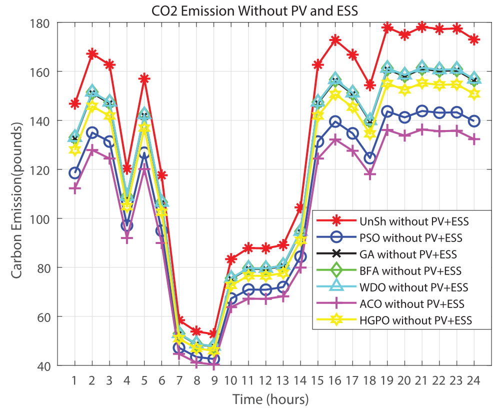

FIGURE 19. carbon emission reduction in scenario 1.

TABLE 5. Comparison of Scenario 1 PAR.

Algorithm	PAR	Difference	Reduction(%)
Unscheduled	2.41	-	-
BPSO	2.09	0.32	12.5%
WDO	2.25	0.16	6.63%
BFA	1.6	0.81	32%
GA	1.9	0.51	21.16%
ACO	1.7	0.71	28.46%
HGPO	1.95	0.46	19.08%

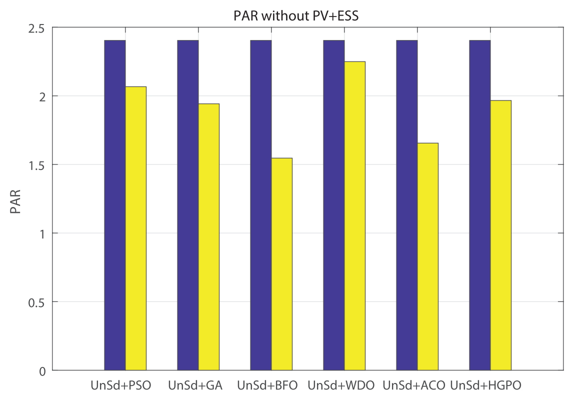

FIGURE 18. PAR reduction in scenario 1.

new peaks. The new peaks that are generated disturbs the whole operational schedule of the electric utility companies (EUCs) and the electric utility companies (EUCs) impose a penalty on that user. However, the ACO and HGPO algorithms uniformly distributes the load and achieves the desired objective. The comparison of PAR in scenario 1 is shown in Table 5.

3) CARBON EMISSION

The corresponding carbon emission of scheduled and unscheduled load without ESS and PV, is illustrated in Figure 19. Results show that carbon emission of heuristic algorithms has efficiently been reduced when compared with that of the unscheduled load. In GA, the value of maximum carbon emission is 161 pounds in time slot 21. In the case of HGPO, it is 155 pounds in time slot 22 and 19, while in the case of WDO, it is 159 pounds in time slot 20. In BFA based scheduling, it is 156 pounds in time slot 18, while in the case of BPSO, it is 143 pounds in time slot 21 and 23. In the case of ACO, it is 136 pounds in time slot 22 respectively.

The total carbon emission in unscheduled load using PV and ESS is 3211 pounds. In the case of GA, HGPO, WDO, BFA, BPSO and ACO, it is 2906, 2791, 2892, 2875, 2588 and 2445 pounds respectively. As a result, the total carbon emission is reduced by 9.49% in GA, 13.08% in HGPO, 9.93% in WDO, 10.46% in BFA, 19.40% in the case of BPSO and 23.85% in the case of ACO. However, the ACO algorithm gives the best result in reducing carbon emission in this scenario. The comparison of carbon emission in scenario 1 is shown in Table 6.

B. SCENARIO 2

In this scenario, the integration of only PV into the residential area is calculated in terms of electricity bill, PAR and carbon emission.

1) ELECTRICITY COST

Figure 20 illustrates the electricity cost of scheduled and unscheduled load with PV only. In BPSO, the maximum cost of electricity is 45 cents in the time slot 20 and 22. In WDO, the maximum cost of electricity is 46 cents in the time slot 19. While in ACO, it is 42 cents in the time slot 20. In the case of HGPO, it is 43 cents in the time slot 20. While in the case of BFA, it is 44 cents in time slot 19. For the GA based scheduled load, it is 39 cents in the time slot 8. The result of BPSO algorithm in terms of electricity bill minimization is better than other heuristic algorithms.

The overall electricity cost in unscheduled load is 687 cents, while using ACO, BPSO, WDO, GA, HGPO and BFA are 588.45, 535, 610, 611, 584 and 608 cents, respectively. Overall electricity cost illustrates that ACO, BPSO, GA, WDO, HGPO and BFA minimizes the electricity cost

TABLE 6. Comparison of Scenario 1 carbon emission.

Algorithm	Carbon emissions(pounds)	Difference(pounds)	Reduction(%)
Unscheduled	3211	-	-
BPSO	2588	623	19.40%
WDO	2892	319	9.93%
BFA	2875	336	10.46%
GA	2906	305	9.49%
ACO	2445	766	23.85%
HGPO	2791	420	13.08%

TABLE 7. Comparison of Scenario 2 Cost.

Algorithm	Cost(cents)	Difference(cents)	Reduction(%)
Unscheduled	687	-	-
BPSO	535	152	22.12%
WDO	610	77	10.93%
BFA	608	79	11.49%
GA	611	76	11.06%
ACO	588.45	98.55	13.44%
HGPO	584	103	14.99%

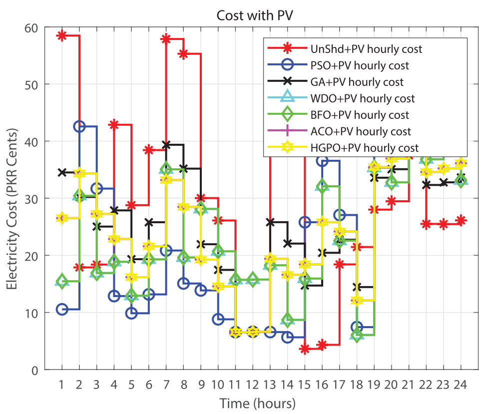

FIGURE 20. Cost reduction in scenario 2.

TABLE 8. Comparison of Scenario 2 PAR.

Algorithm	PAR	Difference	Reduction(%)
Unscheduled	2.3	-	-
BPSO	2	0.0.3	9.90%
WDO	1.65	0.65	22.72%
BFA	1.64	0.66	27.27%
GA	1.66	0.64	22.72%
ACO	1.15	1.08	34.38%
HGPO	1.75	0.55	21.77%

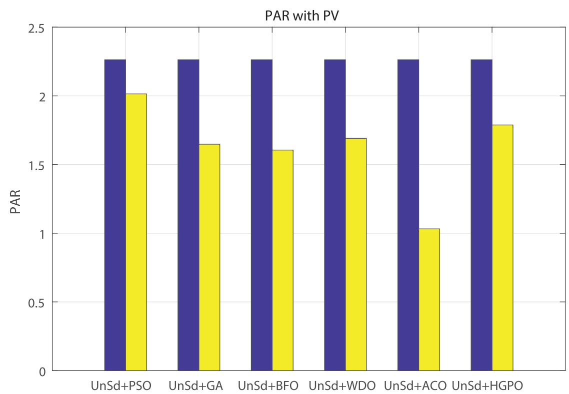

FIGURE 21. PAR reduction in scenario 2.

by 13.44%, 22.12%, 11.06%, 10.93%, 14.99% and 11.49%, respectively. Nevertheless, when complete cost minimization is considered, the BPSO algorithm gives best results when compared with other algorithms. The comparison of cost in scenario 2 is shown in Table 7.

2) PAR

Figure 21 illustrates the PAR of unscheduled and scheduled load. Results show that the proposed ACO algorithm reduces PAR by 34.38%. BPSO, BFA, WDO, GA and HGPO also minimize the PAR by 9.90%, 27.27%, 22.72%, 21.77% and 18.18%, respectively. Although, these algorithms reduce PAR and avert peak creation, the WDO and BFA algorithms mostly shifts the users load to off-peak hours and build new peaks. These newly formed peaks disturb the whole operational schedule of the electric utility companies (EUCs) and the electric utility companies (EUCs) impose a penalty on the user. However, the BPSO and HGPO algorithms uniformly distribute the load and achieve the desired objective. The comparison of PAR in scenario 2 is shown in Table 8.

3) CARBON EMISSION

The corresponding carbon emission of scheduled and unscheduled load with PV only is illustrated in Figure 22. The result shows that carbon emission of heuristic algorithm is efficiently reduced when compared with unscheduled load. In GA, the value of maximum carbon emission is 132 pounds in time slot 20. In the case of HGPO, it is 127 pounds in time slot 21, while in the case of WDO, it is 139 pounds in time slot 20. In BFA based scheduling, it is 140 pounds in time slot 18, while in the case of BPSO, it is 117 pounds in time slot 21 and 23. In the case of ACO, it is 112 pounds in time slot 22 respectively.

TABLE 9. Comparison of Scenario 2 Carbon emissions.

Algorithm	Carbon emissions(pounds)	Difference(pounds)	Reduction(%)
Unscheduled	2722	-	-
BPSO	2103	619	22.74%
WDO	2498	224	8.22%
BFA	2510	212	7.78%
GA	2411	311	11.42%
ACO	2068	654	24.02%
HGPO	2293	429	15.76%

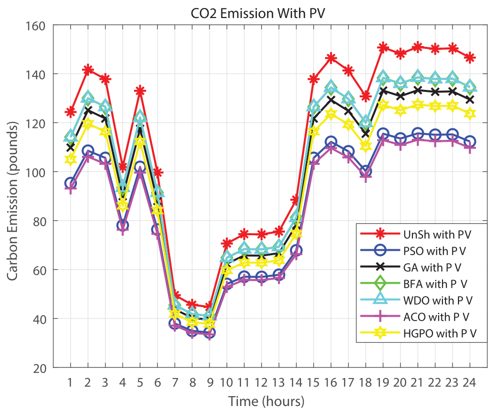

FIGURE 22. Carbon emissions reduction in scenario 2.

The total carbon emission in unscheduled load using PV and ESS is 2722 pounds. In the case of GA, HGPO, WDO, BFA, BPSO and ACO, it is 2411, 2293, 2498, 2510, 2103 and 2068 pounds respectively. As a result, the total carbon emission is reduced by 11.42% in the case of GA, 15.76% in HGPO, 8.22% in WDO, 7.78% in BFA, 22.74% in the case of BPSO and 24.02% in the case of ACO. However, the ACO algorithm gives the best result in reducing carbon emission. The comparison of carbon emission in scenario 2 is shown in Table 9.

C. SCENARIO 3

In this scenario, the integration of ESS and PV into the local area is evaluated in terms of electricity bill, PAR, carbon emissions and UC.

1) ELECTRICITY COST

Figure 23 shows the electricity cost of schedule and unscheduled load with ESS and PV. Results shows that our proposed algorithms (GA, BFA,BPSO, ACO, HGPO, WDO) have scheduled load efficiently. The maximum electricity bill in GA based scheduling is 39.2 cents in the time slot 8. In BPSO, the maximum cost of electricity is 43 cents in the time slot 3. In BFA, the value of maximum cost of electricity is 62.6 cents in time the slot 8. While, in the case of WDO, the maximum cost of electricity is 44 cents in the time slot 23. In ACO based scheduling, it is 37 cents in time slot 7, while in the case of HGPO, it is 37 cents in time slot 21.

TABLE 10. Comparison of Scenario 3 Cost.

Algorithm	Cost(cents)	Difference(cents)	Reduction(%)
Unscheduled	716	-	-
BPSO	533	183	25.55%
WDO	605	111	15.50%
BFA	615	101	14.10%
GA	626	90	12.56%
ACO	564	152	21.22%
HGPO	595	121	16.89%

TABLE 11. Comparison of Scenario 3 PAR.

Algorithm	PAR	Difference	Reduction(%)
Unscheduled	2.4	-	-
BPSO	1.3	1.1	36.98%
WDO	1.65	0.75	26.87%
BFA	1.9	0.5	19.50%
GA	1.85	0.55	22.68%
ACO	2.17	0.23	7.94%
HGPO	1.6	0.8	30.05%

The total bills observed while implementing heuristic algorithm in unscheduled and scheduled loads are: 716 cents in unscheduled, 533 cents in BPSO, 626 cents in GA, 605 cents in WDO, 615 cents in BFA, 564 cents in ACO and 595 cents in HGPO respectively. In contrast of overall electricity cost, the BPSO, GA, BFA, WDO, HGPO and ACO algorithms based HPEMC minimize electricity cost by 25.55%, 12.56%, 15.50%, 14.10%, 21.22% and 16.89% respectively. Here, BPSO gives the best results when compared with other algorithms. The comparison of cost in scenario 3 is shown in Table 10.

2) PAR

Figure 24 illustrates the PAR of unscheduled and scheduled load. Results illustrate that the proposed GA, BPSO, BFA, WDO, ACO and HGPO algorithms minimize the PAR by 22.68%, 36.98%, 19.50%, 26.87%, 7.94% and 30.05%, respectively. However, the BPSO algorithm reduces the PAR substantially more than the other heuristic algorithms. The WDO and GA mostly shifts the users load to off-peak hours and builds new peaks. However, the BPSO and HGPO algorithms distribute the load uniformly and achieve the desired

TABLE 12. Comparison of Scenario 3 Carbon emissions.

Algorithm	Carbon emissions(pounds)	Difference(pounds)	Reduction(%)
Unscheduled	2626	-	-
BPSO	2029	597	22.73%
WDO	2304	322	11.18%
BFA	2299	327	11.34%
GA	2293	333	12.68%
ACO	2234	392	14.88%
HGPO	2228	398	15.15%

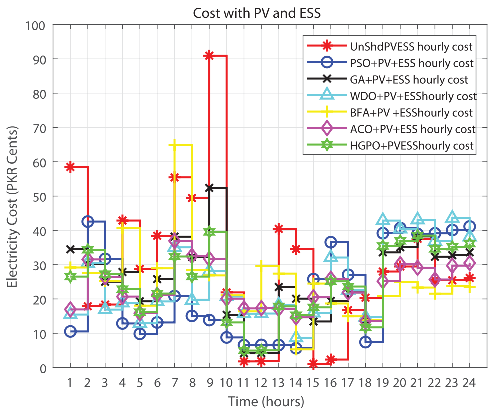

FIGURE 23. Cost reduction in scenario 3.

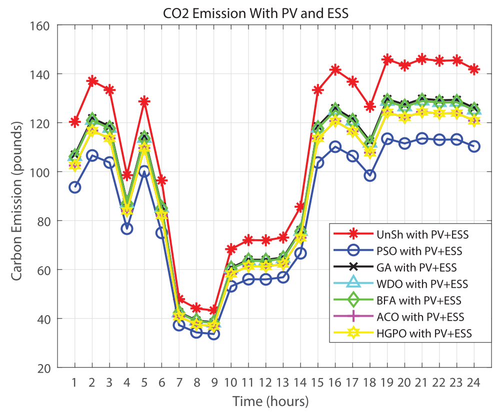

FIGURE 25. Carbon emissions reduction in scenario 3.

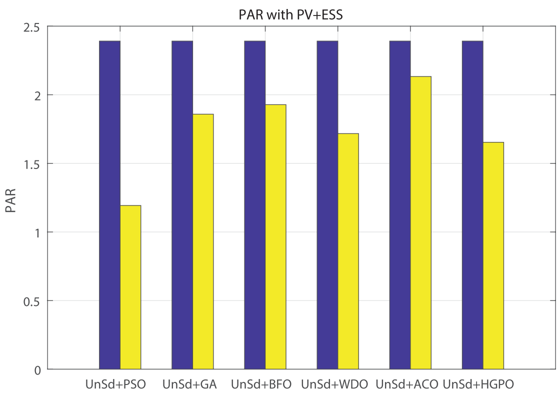

FIGURE 24. PAR reduction in scenario 3.

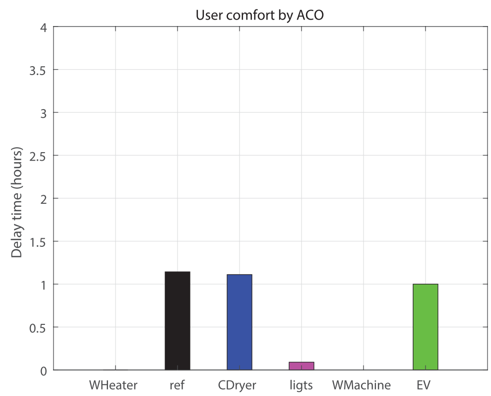

FIGURE 26. UC by ACO.

objective. The comparison of PAR in scenario 3 is shown in Table 11.

3) CARBON EMISSIONS

The corresponding carbon emissions of scheduled and unscheduled load with ESS and PV is illustrated in Figure 25. Results show that carbon emissions of heuristic algorithms is being reduced more than that of unscheduled load. In GA based scheduling, the value of maximum carbon emissions is 129 pounds in time slot 19 and 21. In the case of BPSO it is 112 pounds in time slot 23. The BFA based scheduled load has maximum carbon emissions value of 131 pounds in time slot 20, while in the case of HGPO it is 123 pounds in time slot 18 and 21. In WDO based scheduling, it is 132 pounds in time slot 22, while in the case of ACO, it is 124 pounds in time slot 21 respectively.

The total carbon emissions in unscheduled load using PV and ESS is 2626 pounds. In GA, BPSO, BFA, HGPO, WDO and ACO it is 2293, 2029, 2299, 2228, 2304 and 2234 pounds, respectively. As a result, the total carbon emissions is reduced by 12.68% in the case of GA, 22.73% in BPSO, 11.34% in BFA, 15.15% in HGPO, 11.18% in the case of WDO and 14.88% in the case of ACO. However, the BPSO algorithm gives the best result in reducing the carbon emissions

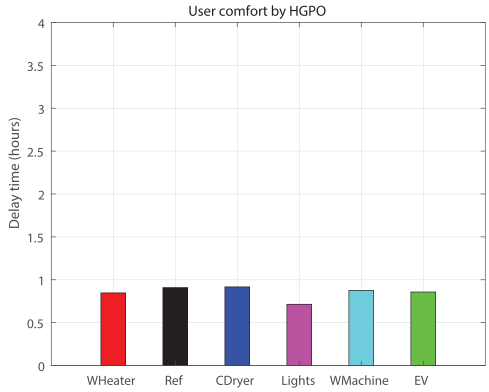

FIGURE 27. UC by HGPO.

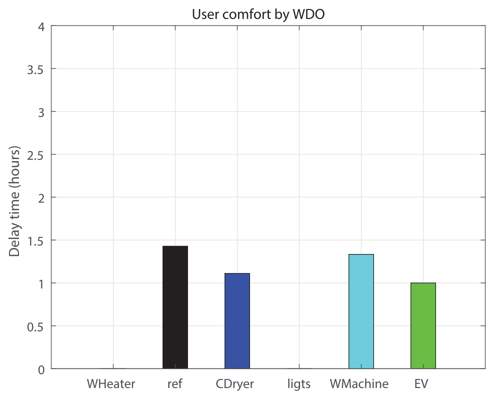

FIGURE 28. UC by WDO.

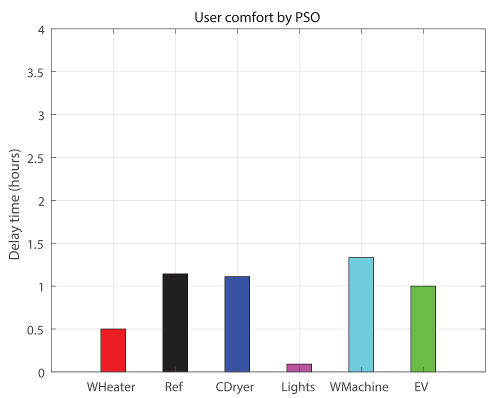

FIGURE 29. UC by PSO.

TABLE 13. UC waiting time.

Algorithm	Appliance	Waiting time (minutes)
BPSO	Water heater	30
	Refrigerator	70
	CD player	67
	Lights	10
	Washing machine	80
	EV	60
WDO	Water heater	0
	Refrigerator	85
	CD player	70
	Lights	0
	Washing machine	80
	EV	60
BFA	Water heater	75
	Refrigerator	100
	CD player	85
	Lights	50
	Washing machine	70
	EV	60
GA	Water heater	0
	Refrigerator	40
	CD player	90
	Lights	0
	Washing machine	120
	EV	60
ACO	Water heater	0
	Refrigerator	70
	CD player	66
	Lights	5
	Washing machine	0
	EV	60
HGPO	Water heater	45
	Refrigerator	50
	CD player	55
	Lights	40
	Washing machine	54
	EV	54

when compared with all other heuristic algorithms. The comparison of carbon emissions in scenario 3 is shown in Table 12.

4) USER COMFORT

Electricity bill and waiting time, both are related to UC. UC is calculated in terms of waiting time in this paper. Waiting time is the time that user waits to turn on an appliance. Users must operate their appliances according to the desired scheduling, for lower electricity bill. If a user is more interested in reducing the cost, he will have to compromise his comfort. Figure 26, 27, 28, 29, 30 and 31 illustrates the average waiting time of ACO, HGPO, WDO, PSO, BFA and GA algorithms. Results show that ACO have less waiting time in comparison to other algorithms. GA and WDO shows no waiting time in case of lights and water heater. HGPO algorithm shows less than 1 hour waiting time in all cases. PSO and BFA algorithms show some waiting time in all cases. Table 13 shows the waiting time of all the appliances.

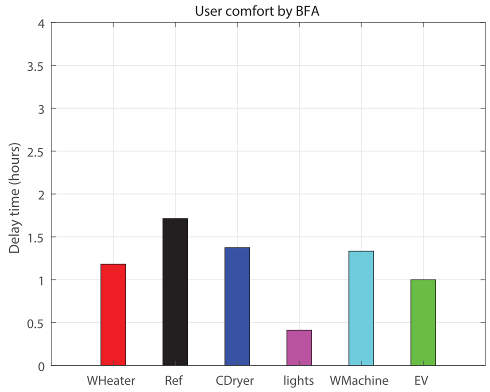

FIGURE 30. UC by BFA.

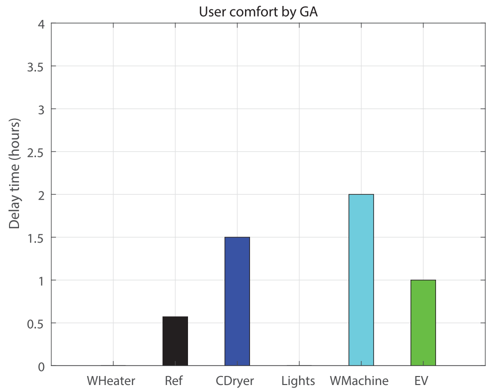

FIGURE 31. UC by GA.

VI. CONCLUSION

We proposed an energy management system to reduce the electricity bill for the residential area. Minimization of carbon emissions, reduction in PAR, and increasing UC are also the peripheral outcomes of our work. We considered a smart home that had different smart appliances. The smart home was also integrated with RESs. Also, the energy storage system was considered to utilize energy efficiently. Moreover, we have solved the appliance scheduling problem by using GA, WDO, BPSO, BFA, ACO, and HGPO algorithms. Simulation results verified that the proposed algorithm efficiently schedule smart appliances. As a result, by implementing our proposed algorithm, the electricity bill was minimized by 25.55%, PAR reduced by 36.98%, and carbon emissions reduced by 24.02%. In our future work, we will use different algorithms and compare them with our proposed algorithm. We will also use an electric vehicle for storage and wind turbine as RESs.

REFERENCES

[1] *World Nuclear Association*. Accessed: Jan. 10, 2020. [Online]. Available: https://www.world-nuclear.org/nuclear-essentials/where-does-our-electricity-come-from.aspx

[2] L. M. Camarinha-Matos, "Collaborative smart grids–a survey on trends," *Renew. Sustain. Energy Rev.*, vol. 65, pp. 283–294, Nov. 2016.

[3] H. Sawall, A. Scheuriker, and D. Stetter, "Flexibility definition for smart grid cells in a decentralized energy system," in *Proc. 7th Int. Conf. Smart Cities Green ICT Syst.*, 2018, pp. 130–139.

[4] M. M. Hossain, K. R. Zafreen, A. Rahman, M. A. Zamee, and T. Aziz, "An effective algorithm for demand side management in smart grid for residential load," in *Proc. 4th Int. Conf. Adv. Electr. Eng. (ICAEE)*, Sep. 2017, pp. 336–340.

[5] X. Jiang and C. Xiao, "Household energy demand management strategy based on operating power by genetic algorithm," *IEEE Access*, vol. 7, pp. 96414–96423, 2019.

[6] T. Sattarpour, D. Nazarpour, and S. Golshannavaz, "A multi-objective HEM strategy for smart home energy scheduling: A collaborative approach to support microgrid operation," *Sustain. Cities Soc.*, vol. 37, pp. 26–33, Feb. 2018.

[7] A. Ahmad, A. Khan, N. Javaid, H. M. Hussain, W. Abdul, A. Almogren, A. Alamri, and I. Azim Niaz, "An optimized home energy management system with integrated renewable energy and storage resources," *Energies*, vol. 10, no. 4, p. 549, Apr. 2017.

[8] H. Nguyen, C. Zhang, and M. A. Mahmud, "Smart charging and discharging of electric vehicles to support grid with high penetration of renewable energy," *IFAC Proc. Volumes*, vol. 47, no. 3, pp. 8604–8609, 2014.

[9] Z. Yahia and A. Pradhan, "Optimal load scheduling of household appliances considering consumer preferences: An experimental analysis," *Energy*, vol. 163, pp. 15–26, Nov. 2018.

[10] A. Aktas, K. Erhan, S. Özdemir, and E. Özdemir, "Dynamic energy management for photovoltaic power system including hybrid energy storage in smart grid applications," *Energy*, vol. 162, pp. 72–82, Nov. 2018.

[11] A. Najafi-Ghalelou, S. Nojavan, and K. Zare, "Information gap decision theory-based risk-constrained scheduling of smart home energy consumption in the presence of solar thermal storage system," *Sol. Energy*, vol. 163, pp. 271–287, Mar. 2018.

[12] S. Lee, J. Lee, H. Jung, J. Cho, J. Hong, S. Lee, and D. Har, "Optimal power management for nanogrids based on technical information of electric appliances," *Energy Buildings*, vol. 191, pp. 174–186, May 2019.

[13] X. Wu, X. Hu, Y. Teng, S. Qian, and R. Cheng, "Optimal integration of a hybrid solar-battery power source into smart home nanogrid with plug-in electric vehicle," *J. Power Sources*, vol. 363, pp. 277–283, Sep. 2017.

[14] S. Golshannavaz, "Cooperation of electric vehicle and energy storage in reactive power compensation: An optimal home energy management system considering PV presence," *Sustain. Cities Soc.*, vol. 39, pp. 317–325, May 2018.

[15] N. Amjady, F. Keynia, and H. Zareipour, "Short-term load forecast of microgrids by a new bilevel prediction strategy," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 286–294, Dec. 2010.

[16] V. Mnih, H. Larochelle, G. Hinton, "Conditional restricted Boltzmann machines for structured output prediction," in *Proc. Int. Conf. Uncertainty Artif. Intell.*, 2011, pp. 1–9.

[17] F. K. Arabul, A. Y. Arabul, C. F. Kumru, and A. R. Boynuegri, "Providing energy management of a fuel cell–battery–wind turbine–solar panel hybrid off grid smart home system," *Int. J. Hydrogen Energy*, vol. 42, no. 43, pp. 26906–26913, 2017.

[18] M. Rastegar, M. Fotuhi-Firuzabad, and H. Zareipour, "Home energy management incorporating operational priority of appliances," *Int. J. Electr. Power Energy Syst.*, vol. 74, pp. 286–292, Jan. 2016.

[19] M. S. Ahmed, A. Mohamed, T. Khatib, H. Shareef, R. Z. Homod, and J. A. Ali, "Real time optimal schedule controller for home energy management system using new binary backtracking search algorithm," *Energy Buildings*, vol. 138, pp. 215–227, Mar. 2017.

[20] X. Jin, K. Baker, D. Christensen, and S. Isley, "Foresee: A user-centric home energy management system for energy efficiency and demand response," *Appl. Energy*, vol. 205, pp. 1583–1595, Nov. 2017.

[21] R. Zafar, A. Mahmood, S. Razzaq, W. Ali, U. Naeem, and K. Shehzad, "Prosumer based energy management and sharing in smart grid," *Renew. Sustain. Energy Rev.*, vol. 82, pp. 1675–1684, Feb. 2018.

[22] R. Tang, S. Wang, and H. Li, "Game theory based interactive demand side management responding to dynamic pricing in price-based demand response of smart grids," *Appl. Energy*, vol. 250, pp. 118–130, Sep. 2019.

[23] M. Killian, M. Zauner, and M. Kozek, "Comprehensive smart home energy management system using mixed-integer quadratic-programming," *Appl. Energy*, vol. 222, pp. 662–672, Jul. 2018.

[24] R.-S. Liu and Y.-F. Hsu, "A scalable and robust approach to demand side management for smart grids with uncertain renewable power generation and bi-directional energy trading," *Int. J. Electr. Power Energy Syst.*, vol. 97, pp. 396–407, Apr. 2018.

[25] G. R. Aghajani, H. A. Shayanfar, and H. Shayeghi, ''Demand side management in a smart micro-grid in the presence of renewable generation and demand response,'' *Energy*, vol. 126, pp. 622–637, May 2017.

[26] H. Chamandoust, G. Derakhshan, S. M. Hakimi, and S. Bahramara, ''Tri-objective scheduling of residential smart electrical distribution grids with optimal joint of responsive loads with renewable energy sources,'' *J. Energy Storage*, vol. 27, Feb. 2020, Art. no. 101112.

[27] M. Hu, J.-W. Xiao, S.-C. Cui, and Y.-W. Wang, ''Distributed real-time demand response for energy management scheduling in smart grid,'' *Int. J. Electr. Power Energy Syst.*, vol. 99, pp. 233–245, Jul. 2018.

[28] B. Lokeshgupta and S. Sivasubramani, ''Multi-objective home energy management with battery energy storage systems,'' *Sustain. Cities Soc.*, vol. 47, May 2019, Art. no. 101458.

[29] V. Davatgaran, M. Saniei, and S. S. Mortazavi, ''Smart distribution system management considering electrical and thermal demand response of energy hubs,'' *Energy*, vol. 169, pp. 38–49, Feb. 2019.

[30] Z. Zhao, W. Cheol Lee, Y. Shin, and K.-B. Song, "An optimal power scheduling method for demand response in home energy management system," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1391–1400, Sep. 2013.

[31] Z. A. Khan, A. Zafar, S. Javaid, S. Aslam, M. H. Rahim, and N. Javaid, ''Hybrid meta-heuristic optimization based home energy management system in smart grid,'' *J. Ambient Intell. Humanized Comput.*, vol. 10, no. 12, pp. 4837–4853, Dec. 2019.

[32] S. Aslam, A. Khalid, and N. Javaid, ''Towards efficient energy management in smart grids considering microgrids with day-ahead energy forecasting,'' *Electric Power Syst. Res.*, vol. 182, May 2020, Art. no. 106232.

[33] D. Dabhi and K. Pandya, ''Enhanced velocity differential evolutionary particle swarm optimization for optimal scheduling of a distributed energy resources with uncertain scenarios,'' *IEEE Access*, vol. 8, pp. 27001–27017, 2020.

[34] W. Wang, B. Lou, X. Li, X. Lou, N. Jin, and K. Yan, ''Intelligent maintenance frameworks of large-scale grid using genetic algorithm and K-Mediods clustering methods,'' *World Wide Web*, vol. 23, no. 2, pp. 1177–1195, Mar. 2020.

[35] O. Abdalla, H. Rezk, and E. M. Ahmed, ''Wind driven optimization algorithm based global MPPT for PV system under non-uniform solar irradiance,'' *Sol. Energy*, vol. 180, pp. 429–444, Mar. 2019.

[36] G. Hafeez, K. S. Alimgeer, Z. Wadud, I. Khan, M. Usman, A. B. Qazi, and F. A. Khan, "An innovative optimization strategy for efficient energy management with day-ahead demand response signal and energy consumption forecasting in smart grid using artificial neural network," *IEEE Access*, vol. 8, pp. 84415–84433, 2020, doi: 10.1109/ACCESS.2020.2989316.

[37] G. Hafeez, K. S. Alimgeer, A. B. Qazi, I. Khan, M. Usman, F. A. Khan, and Z. Wadud, "A hybrid approach for energy consumption forecasting with a new feature engineering and optimization framework in smart grid," *IEEE Access*, vol. 8, pp. 96210–96226, 2020, doi: 10.1109/ACCESS.2020.2985732.

[38] G. Hafeez, N. Javaid, S. Iqbal, and F. A. Khan, ''Optimal residential load scheduling under utility and rooftop photovoltaic units,'' *Energies*, vol. 11, no. 3, p. 611, 2018.

[39] N. Javaid, G. Hafeez, S. Iqbal, N. Alrajeh, M. S. Alabed, and M. Guizani, ''Energy efficient integration of renewable energy sources in the smart grid for demand side management,'' *IEEE Access*, vol. 6, pp. 77077–77096, 2018.

[40] A. Pehlken, A. Decker, C. Kottowski, A. Kirchner, and K.-D. Thoben, ''Energy efficiency in processing of natural raw materials under consideration of uncertainties,'' *J. Cleaner Prod.*, vol. 106, pp. 351–363, Nov. 2015.

ADIL IMRAN is currently pursuing the B.Sc. degree in electrical engineering with the University of Engineering and Technology, Mardan, Mardan, Pakistan. He has authored/coauthored over in peer-reviewed research articles in reputed international journals and conferences. His research interests include optimization, planning, energy management, and machine learning applications in smart grids/microgrids.

GHULAM HAFEEZ received the B.Sc. degree in electrical engineering from the University of Engineering and Technology, Peshawar, Pakistan, and the M.S. degree in electrical engineering from COMSATS University Islamabad, Pakistan, where he is currently pursuing the Ph.D. degree. He is also a Lifetime Chartered Engineer with Pakistan Engineering Council. He is also working as a Lecturer with the Department of Electrical Engineering, University of Engineering and Technology, Mardan, Mardan. He has authored or coauthored over 15 peer-reviewed research articles in reputed international journals and conferences. His research interests include optimization, planning, energy management, and machine learning applications in smart/micro grids.

IMRAN KHAN (Senior Member, IEEE) received the B.Sc. degree in electrical engineering from the NWFP University of Engineering and Technology, Peshawar, Pakistan, in 2003, the M.Sc. degree in telecommunication engineering from the Asian Institute of Technology, Thailand, in 2007, and the Ph.D. degree from the Telecommunications FOS, School of Engineering and Technology, Asian Institute of Technology, Thailand, in 2010. He is currently working as a Professor with the Department of Electrical Engineering, University of Engineering and Technology, Mardan, Mardan. His research interests include performance analysis of wireless communication systems, OFDM, OFDMA, MIMO, cooperative networks, cognitive radio systems, and energy management in the smart grid.

MUHAMMAD USMAN (Senior Member, IEEE) received the B.Sc. degree in computer information systems engineering from the University of Engineering and Technology (UET), Peshawar, Pakistan, in 2004, the M.Sc. degree in computer engineering from the Center of Advanced Studies in Engineering (CASE), Islamabad, Pakistan, in 2007, and the Ph.D. degree from the University of Ulsan, South Korea, in 2016. He is currently an Associate Professor with UET, Mardan. In 2015, he received best SCI(E) paper award from the Korean Government through BK21+ project. He is the reviewer of various reputable international journals, such as the IEEE Transactions on Wireless Communications, IEEE Access, the IEEE Transactions on Cognitive Communication and Networking, *IEEE Sensors Journal*, *IEEE Systems Journal*, *Applied Mathematics & Information Sciences*, and *The Computer Journal*. His research interests include security and energy efficiency in wireless networks, next-generation networks, and wireless sensor networks.

ZEESHAN SHAFIQ received the bachelor's, master's, and Ph.D. degrees in electrical engineering from the University of Engineering and Technology, Peshawar, in 2009, 2012, and 2018, respectively. His research interests include vehicular ad hoc networks, intelligent transportation systems, and unmanned aerial vehicles. He has also reviewed many research articles for well-reputed journals, including IEEE Access and IEEE Technical Review journals. He was a recipient of the International Research Support Initiative Program Scholarship from the Higher Education Commission Pakistan for visiting The University of Sydney, Australia. During his stay, he was involved in UAV at the Centre of Excellence in Telecommunications.

ABDUL BASEER QAZI (Member, IEEE) received the M.S. degree in information and communication systems from the University of Technology, Hamburg, Germany, and the Ph.D. degree from UNU-MERIT, University of Maastricht, The Netherlands. He is currently an Associate Professor with the Department of Software Engineering, Bahria University, Islamabad, Pakistan. Prior to this, he was an Assistant Professor with the Capital University of Science and Technology, Islamabad. He also worked as an Assistant Professor with CECOS University, Peshawar, Pakistan. His industrial experiences include working for four Fortune 500 companies, IBM, Siemens, Philips Medical Systems, and NXP Semiconductors in Germany and The Netherlands. His research interests include wireless networks, antennas, technology policy, innovation, and entrepreneurship.

AZFAR KHALID received the B.Sc. degree in mechanical engineering from the GIK Institute, Pakistan, in 2000, and the Ph.D. degree in precision engineering and robotics from The University of Manchester, U.K., in 2009. He is currently a Senior Lecturer of industrial robotics and controls with Nottingham Trent University, U.K. Prior to this, he has worked in the Capital University of Science and Technology (CUST) and the National University of Science and Technology (NUST), Islamabad, Pakistan. He has also worked as a Research Associate in the Bremen Institute for Production and Logistics (BIBA), Bremen, Germany, where his research focus was cyber physical system development for human robot collaboration in the context of Industry 4.0. His research interests include precision engineering, robotics and control systems, cyber physical systems, and human robot collaboration. He is a Chartered Engineer (CEng), a member of Institute of Mechanical Engineers (MIMechE), U.K., and an Associate Fellow of Higher Education Academy (AFHEA).

KLAUS-DIETER THOBEN is currently a Professor for integrated product development with the Faculty of Production Engineering, University of Bremen, Germany. He is also the Managing Director and a Spokesperson of the Bremen Institute for Production and Logistics (BIBA). He has been involved in research for ICT applications in production and logistics as well as product development and lifecycle from the last 20 years. Furthermore, he is the representative of the University of Bremen in several boards, such as wind energy, logistics, and product development. He has more than 20 years of experience of working in large international research projects and has also managed several projects at national and international level. His teaching domain is related to product design and development as well on organizational issues related to distributed production. He has authored numerous journal contributions and edited several books. Major publications address co-operative processes with a specific focus on product-based innovations, product and service engineering, product lifecycle management, and collaborative enterprise networks.