IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received May 21, 2021, accepted June 2, 2021, date of publication June 7, 2021, date of current version June 17, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3087321

An Optimal Power Usage Scheduling in Smart Grid Integrated With Renewable Energy Sources for Energy Management

ATEEQ UR REHMAN[1], ZAHID WADUD[1], RAJVIKRAM MADURAI ELAVARASAN[2], GHULAM HAFEEZ[3,4], IMRAN KHAN[3], (Senior Member, IEEE), ZEESHAN SHAFIQ[3], AND HASSAN HAES ALHELOU[2,5], (Senior Member, IEEE)

[1]Department of Computer System Engineering, University of Engineering and Technology, Peshawar 25000, Pakistan
[2]Clean and Resilient Energy Systems (CARES) Laboratory, Texas A&M University, Galveston, TX 77553, USA
[3]Department of Electrical Engineering, University of Engineering and Technology, Mardan 23200, Pakistan
[4]Department of Electrical and Computer Engineering, COMSATS University Islamabad, Islamabad 44000, Pakistan
[5]Department of Electrical Power Engineering, Faculty of Mechanical and Electrical Engineering, Tishreen University, Latakia 2230, Syria

Corresponding authors: Hassan Haes Alhelou (alhelou@tishreen.edu.sy) and Ghulam Hafeez (ghulamhafeez393@gmail.com)

This work was supported by Tishreen University, Latakia, Syria.

ABSTRACT Existing power grids (PGs) and in-home energy management controllers do not offer its users the choice to maintain comfort and provide a bearable solution in terms of low cost and reduced carbon emission. This work is based on energy usage scheduling and management under electric utility and renewable energy sources i.e., solar energy (SE), controllable heat and power (CHP) and wind energy (WE) together. Efficient integration of renewable energy sources (RES) and battery storage system (BSS) have been suggested to solve the energy management problem, reduce the bill cost, peak-to-average ratio (PAR) and carbon emission. User's electricity bill reduction have been achieved by proposed power usage scheduling method and integrating low cost RESs. PAR minimization have been achieved through shifting the demand in response to real time price from high-peak hours to low-peak hours. In this context, load scheduling and energy storage system management controller (LSEMC) is proposed which is based on heuristic algorithms i.e., genetic algorithm (GA), wind driven optimization (WDO), binary particle swarm optimization (BPSO), bacterial foraging optimization (BFO) and our suggested hybrid of GA, WDO and PSO (HGPDO) algorithm. The performance of the heuristic algorithms and proposed scheme is evaluated numerically. Results demonstrate that our proposed algorithm and the LSEMC reduces the electricity bill, PAR and CO_2 in Case 1, by 58.69%, 52.78% and 72.40%, in Case 2, by 47.55%, 45.02% and 92.90% and in Case 3, by 33.6%, 54.35% and 91.64%, respectively as compared with unscheduled. Moreover, the user comfort by our proposed HGPDO algorithm in terms of delay, thermal, air quality and visual improves by 35.55%, 16.66%, 91.64% and 45%, respectively.

INDEX TERMS Energy management, battery energy storage systems, renewable, hybrid heuristic algorithms, power usage scheduling, smart grid.

NOMENCLATURE

Main Symbols

v_j^t	Velocity of particles at t
F_c	Coriolis force
μ	Inertia factor
Ω	Earth rotation
α_c	coefficient of friction
ρ	Air density
F_f	Friction force
F_{pg}	Friction gradient
F_g	Gravitational force
δ_v	Finite volume of the air
Δ	Pressure gradient
z	Ant
g	Acceleration due to gravity
v	Smart home
x	Set
M	Set of shift-able appliances
T	Time interval

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

t	Time slot
N	Set of non-shiftable appliances
v_i^t	Current velocity at t
P_{sch}	Power scheduling matrix
A	All appliances
DTR	Delay time rate
N_{gmax}	Maximum iteration
ρ^{DTRa}	Total DTR
X_{gbest}^{t-1}	Global best position
$E_{ex}(t)$	Energy purchased from external grid
L_t	Total load
L_{bill}^{sch}	Schedulable load bill
L_{bill}^{nsch}	Non-schedulable load bill
E_{pv}	PV power
P_{wd}	Wind generation power
E_{bio}	CHP generation power
l	Appliance operation time
α/β	Operation start/end time
η	Price per kWh
γ	Electricity emissions factor
$\phi(t)$	Total RES at time t
E_{pv}	Energy conversion efficiency factor
A_{pv}	Area of panel in (m^2)
$Ir(t)$	Solar irradiance at time slot t
$T_a(t)$	Outdoor temperature at time slot t
ζ	Weighted factor
α_1, α_2	Shape factors
β_1,β_2	Scale factors
A_{tb}	Area of wind turbine blade
$V_s(t)$	Wind speed in m/s at time slot t
∂	Total system efficiency
W_e	CHP electric output
Q_{th}	Total thermal output
L	Lower heating value
Q_f	Fuel input to CHP
Q_{br}	Bio-gas recovery
γ_e	Recovery efficiency
CF	Capacity factor
p_t	EV on-board PV generation
g_t	Remaining energy of p_t
l_τ	EV load at time slot τ
ω	Time constant of HVAC system
η_e	Thermal conversion efficiency
A_c	Overall thermal conductivity

Abbreviations

UC, TC, VC	User, thermal and visual comfort
NSA	Non-schedulable appliances
LOT	Lyapunov optimization technique
SSA	Smart schedulable appliances
BPSO, PSO	Binary/particle swarm optimization
PAR	Peak to average ratio
EP	Electricity price
RTP	Real time price
GA	Genetic algorithm
WDO	Wind driven optimization
HEMS	Home energy management system
SG, MG	Smart grid, micro grid
HGPDO	Hybrid-GA, PSO and WDO

I. INTRODUCTION

With the growth of population and development, it is estimated that the energy demand may grow by 3% at the end of year 2021 [1]. Traditional power grids (PGs) powered by fuels, produce 64.5% of power worldwide. These PGs emit a larger amount of carbon, where the generation sector and transport sector almost release 40% and/ 24% carbon respectively [2]. According to the Energy Information Administration (EIA), the average electric bill for U.S. households could increase by 2.3% next year [3]. This drastic increase in demand and cost will result int the need to generate electricity from alternative sources like solar, thermal, and wind. Moreover, to cover the exponential increase in energy demand, reduce carbon emission and low cost, researchers have suggested new means of power generation by renewable energy sources (RES) [4]. To efficiently use these RES, we need to renovate traditional PGs into smart grids (SGs). SG has the ability to meet growing demands and incorporate new RES together. SG incorporate modern communication infrastructure with existing grid to efficiently use available energy sources at site [5].

At user end, there is absence of energy management and load scheduling. Moreover, at traditional PGs, there is lack of communication infrastructure. Besides, due to excess emission of carbon from fuel based PGs, a rise in the environmental pollution has occurred [31]. It is not feasible for the consumers to change the schedule of their electric appliances by compromising comfort level. Accordingly, the LSEMC is required, which smartly schedule the load of home appliances. The main highlights of our research are as follows:

- Efficient Integration of power storage systems and generation systems i.e., BSS, solar, thermal, WE, electric vehicles storage system (EVSS) and external electric grid (EEG) have been suggested to solve the problem of energy management.
- The SE, CHP, WE, BSS, EVs and domestic consumption is made controllable so that the management of power is possible.
- To reduce power consumption form EEG in response to RTP which narrows and shifts load in peak hours.
- Procurement of energy from low price systems i.e. SE, CHP and wind to reduce the user electricity bill.
- Efficient BSS integration and utilization of EVSS in peak hours.
- Maximize user comfort (UC) by minimize delay (delay is the waiting duration to serve the appliances).
- PAR and CO_2 emission percentage reduction.
- Average UC maximization in terms of delay, visual comfort (VC) and thermal comfort (TC).
- Scheduling HVAC which uses almost 50% of the load [25], in such a way to not compromise the TC and achieve less delay comfort and bill as compared with the unscheduled.

The remaining work is organized as follows: section II presents the related works, section III explains the proposed algorithms, section IV describes the proposed system model

TABLE 1. Related work summary.

Reference No	Techniques	Objectives	Limitations/Research gaps
[6]	ANN	Integrate RESs to reduce bill and carbon emission	BSS and UC is ignored
[7]	GA,WDO	Reduce bill and alleviate PAR	RE integration is not included
[8]	ILP	Schedule appliances and reduce uncertainty	No RES integration and carbon emission reduction included
[9]	MOGA	Reduce operation cost and CO_2 emission	No UC
[10]	LOT	Reduce cost and PAR	No UC and carbon emission
[11]	Multi-objective linearization technique	Reduce cost, and load profile deviation	No UC
[12]	HBFPSO	Curtail cost, PAR and carbon emission	No WE,SE and CHP
[13]- [15]	LOT	Minimize system cost and carbon emission	Applicable to remote area
[16]	Hybrid-WDO, BFA	Minimize cost, PAR and improve comfort	No BSS model included and carbon emission is ignored
[17]	DA-GmEDE	Cost reduction, PAR reduction and UC enhancement	Carbon emission is ignored
[18]	LP	EV smart charge/discharge schedule controller	Cost and carbon emission is not discussed
[19]	UFUV	Energy management and load reduction	No UC and carbon emission reduction included
[20]	CNN	Energy forecasting	UC and BSS model ignored
[21]	ANN	PV integration and reduction bill	Battery cost ignored
[22]	Game theory	PAR and cost reduction	Low comfort
[23]	ML	Demand forecasting	No EMC model
[24]	NN	Shape demand and estimate load	UC is ignored
[25]	LOT	Improve comfort, reduce electricity bill	UC is ignored
[26]	PSO	Integrating RES in virtual plant	No BSS and UC included
[27]	Analytical model	To increase SG potential by integrating RES	No UC included
[28]	ML	Demand forecasting	No EMC model
[29]	CNN	Price prediction, RES and BSS integration	UC is ignored
[30]	MKP, DP	Reduce electricity bill and PAR	BSS model is ignored
[31]	Stochastic, LOT	Optimize power cost	Thermal and visual comfort ignored
[32]	HGPO	Reduce bill, PAR and carbon emission	Low load and no thermal comfort included
[33]	Analytical model	Large BSS integration to PV system	High cost
[34]	Hybrid of GA and ACO	Reduce cost, PAR and carbon emission	No wind generation and less UC achieved
[35]	HGWmEDE	Optimal load scheduling and handle load randomness	No RES and BSS model included
[36]	GA	Shaping load and demand	Comfort is not included

and, section V discusses the simulation results. Section VI concludes the work.

II. RELATED WORKS

Several approaches have been adopted for optimized energy management and load scheduling. Moreover, with the advent of information technology, the demand for power rises day-by-day. In the literature, for enhanced energy management and load scheduling, numerous techniques have been suggested. Providing opportunity for the user to schedule and shift their demand from high peak hours to off peak hours using energy management controllers (EMC). Related work with techniques used, objectives and limitations are summarized in Table 1.

With the SG advancement, a user can reduce the electricity bill charges by integrating the RESs. In [6], the authors discussed an artificial neural network (ANN) based model for the integration of RESs to reduce cost and minimize carbon emission. As a result the energy cost of the consumer is reduced by 35%. However, they ignored the integration of BSS and user comfort in their work. In [7], the authors suggested both GA and WDO and then compared the results. The results showed 29% and 36.2% reduction in the bill cost and PAR respectively. However, they have ignored RESs integration in their work. The authors in [8] suggested the techniques of Harris' Hawk optimization combined with integer linear programming (ILP) to solve the randomness problem and to schedule the user appliances. Authors' main objectives were to analyze cost and the trade-off strategies for user comfort and financial benefits. Their model is adoptable to user requirement and robust levels, however, carbon reduction and RES has been ignored. In [9], to solve the optimization problem, minimize operation cost and carbon emission, the authors suggested techniques of multi-objective genetic algorithm (MOGA). The authors in [10] have considered a smart home, which is connected to a grid while different appliances were drawing energy from external grid. Integration of mix energy system has been discussed which includes energy storages, renewable sources and photo voltaic (PV). Authors in [11] have used a multi-objective linearization approach for home energy management with RES and plug-in hybrid electric vehicle (PHEV). Their objectives were to minimize energy bill and load profile deviation. Nevertheless, user comfort has not considered. In [12], authors have proposed an intelligent approach for demand side management with forecasting and net-metering structure. Their objectives were to reduce cost, PAR and carbon emission. In [13], authors have developed a load scheduling and energy management model for electric vehicle, which was connected to external grid and charging stations. In remote areas, where power grid extendibility is costly and not feasible, the mini grid concept is effective and reliable [14]. The authors in [13]–[15] have worked on management of storage and real-time load scheduling of renewable energy (RE) integrated electric vehicle (EV). Their main objectives were to minimize energy gaining from external grid and charge stations which is parking station, public and home charge stations. Moreover, delay minimization, load scheduling, price reduction of aboard PV, PV efficiency and reduction of battery degradation cost and yearly carbon in air were also their objectives. In [16], authors have proposed a model for IoT-enabled smart home for energy management and load scheduling. Their main objectives were to alleviate peak formation and reduce the cost with constraints of user comfort. In [17], an innovative home EMC based on ANN and day-ahead grey wolf modified enhanced differential evolution algorithm (DA-GmEDE) is suggested. They develop a strategy for energy management with day-ahead demand response and power consumption forecasting in SG. In [18], authors have recommended a smart charge and discharge scheduling algorithm based on linear programming (LP) for EV. However, user comfort, carbon emission and RE integration to grid were ignored. In [19], authors have suggested a nano-grid concept to cater peak demand and reduce blackouts. This model work for residential side to auto disconnect the low priority loads. Their objectives were to reduce system from blackout based on the neighbour level. However, user comfort is not included in system model. In [20], authors have presented a pyramid convolution neural network (CNN) based learning model for energy forecasting. They have suggested that power consumers can be grouped into clusters and then representative system could be designed and trained, which can accurately forecast power load for each customer. In [21], authors have presented a storage management model by installing EV batteries as backup. It further involves integration of EV batteries system to smart grid by adopting MILP formulation. However, battery degradation and capacity were not included in cost reduction. In [22], authors particularize a demand side-management methodology that is useful for households based on ANN. Their model includes PV and energy storage and aim a decision-making system to reduce bill, however, battery degradation cost and user comfort is not considered. In [23], authors suggested a home energy management system model to establish and predict a control system based on mixed-integer quadratic programming (MIQP) technique powered by thermal source. Their main objective was to curtail electricity bill, though RESs were not integrated. In [24], authors have suggested micro-grid concept to run data centers on it, to mitigate carbon emission, reduce bill and power outage issues. They used lyapunov optimization technique (LOT) to design and simulate their system model. In [25], an energy management system for sustainable smart home is suggested with HVAC load and random occupancy. Their objectives were to minimize cost and reduce cost of thermal discomfort using LOT. Although, carbon emission reduction in system model were ignored. In [26], a novel controller for scheduling of appliances and integrating RES in virtual plant have been designed. They have used PSO algorithm to minimize cost in crucial time and prioritize the sustainable resources. In [22], to increase the smart grid potential, they have integrated smart homes with renewable energy. The main objectives were PAR and cost reduction, but the impact of comfort were not considered. In [27], a data focused machine learning (ML) approach applied to model the demand and electricity forecasting have been proposed. However, EMC was not included in this work. In [28], a multi-headed CNN based model for price prediction and integration of RES and BSS with SG were suggested. Their proposed scheme helps to reduce the electricity bill of users by 58.32% and 63.02% through integration of RESs without and with BSS, respectively. In [29], authors have proposed a dynamic programming (DP) based EMC for shifting load of demand side management to optimize the smart home appliances usage pattern. Their objectives were to reduce cost, PAR and maintain UC level. In [30], authors have presented a domestic demand model, which showed all dwelling appliances scheduling pattern for twenty two homes over a year. In [31], a hybrid programmable home management system has been proposed based on PSO and GA algorithm. However, thermal comfort and CHP generation was not included. In [34], authors have suggested an optimal home EMC based on heuristic algorithms. Their objectives were to reduce cost, PAR and integrate RES into the system model. They have achieved 59.06% and 17.40% reduction in bill cost and PAR respectively. In [34], an optimal load scheduling framework based on hybrid gray wolf-modified enhanced differential evolutionary (HGWmEDE) algorithm has been suggested. They scheduled the household load using the output of the forecaster module. In [35], a shaping load techniques based on demand side management for industrial plant has been optimized using GA. It has achieved an overall PAR reduction of 21.91%.

TABLE 2. Algorithms parameters.

Algorithm	Parameters	Values
GA	Number of iterations	200
	Population size	200
	P_m	0.1
	P_c	0.9
	N	11
BPSO	Number of iterations	200
	Swarm size	200
	V_{max}	4
	V_{min}	-4
	W_i	2
	C_1	0.4
	C_2	2
	N	11
WDO	Number of iterations	200
	Population size	200
	dim_{min}	-5
	dim_{max}	5
	V_{min}	-0.3
	V_{max}	0.3
	R_t	3
	n	11
	g	0.2
	a	0.4
BFO	Number of iterations	200
	N_e	24
	N_r	5
	N_c	5
	N_p	30
	N_s	2
	C_i	0.01
	P_{ed}	0.1
	θ	0.1
HGPDO	Same parameters as of GA, PSO and WDO	Same values as of GA, PSO and WDO

III. PROPOSED MODEL

In this section, our proposed model is discussed in detail. The methods which have been adopted have also been summarized. We used BPSO, GA, WDO, BFO and HGPDO, because the said algorithms have heuristic nature and initialization of population, which initially tends to optimal and best solutions and subsequently, fills up to the rest of the population with the random solutions. Previously, LP, ILP, DP, MILP, etc., methods have been adopted for appliances scheduling and multi-objective problems. Nevertheless, these methods cannot handle a bulky number of home appliances and also face several convergence difficulties. GA, BPSO, WDO, HGPDO, BFO algorithm overtakes the classical techniques of optimization, and for solving multi-objective problems it provide various methods. The parameters and their respective values are specified in Table 2.

A. GA

The GA is adopted which is a natural inspired algorithm to find optimal solutions. It randomly generates solutions of population containing a defined number of characters/individuals. Each solution contains a set of all kinds of variables denoted as a chromosome. New solutions can be obtained which contains old and new characteristics by calculating the fitness values, after that selecting individuals, crossover and mutation. A solution of best fitness can be generated after its judgement. The defined GA algorithm is used as taken in [31]. Referring to the selection process, the roulette selection method is used, in which the individual with a better fitness value has a higher probability to be selected for further processing. In general, the chromosomes are exemplified through binary strings and these are taken easy to splitting and recombining. Table 2 shows all parameters with values used in algorithm.

B. BPSO

BPSO is a technique inspired by nature for searching optimal solution inside a search space. Initially, it was presented in form of continuous domain. But, later it was explored to discrete domain. The PSO discrete domain is known as BPSO. It has mainly dependency on four aspects: (i) individual best position of particles, (ii) best global position, (iii) initial velocity and (iv), the initial position amongst all the particles. In BPSO, an exploration space is formed, and a randomly population is initialized and spread in the exploration space. To update the particles velocities in each iteration equation (1) is used in [31]. While the parameters values are in Table 2.

$$\sum_{t=1}^{24}\sum_{i=1}^{I}\sum_{t=1}^{24}\sum_{i=1}^{I} v_i^{t+1} = \sum_{t=1}^{24}\sum_{i=1}^{I} uv_i^t(t) + z_1k_1(X_{lbest}, i(j) + z_2k_2(X_{gbest}, i(j) - x_i^t(j)) \quad (1)$$

In the above equation u is the inertia factor, v_i^t and v_j^t is current velocity and velocity of particle, respectively. k_1 and k_2 are random numbers while, z_1, z_2 are local and global pull, respectively. x is the particle's current position, X_{lbest} and X_{gbest} are the local and global best positions respectively. To map the velocities of particle between 0 and 1, equation (2) is used.

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

C. WDO

WDO is a heuristic based optimization algorithm. It is centered on air particles motion phenomenon in atmosphere. In this technique, an N-dimensional exploration space is formed, in which unlimited particles of air move. In WDO, frictional, gravitational, Coriolis, and pressure gradient forces are involved to control air particles. Each force have their own functions i.e., pressure gradient force and friction force function for shifting the air particles in the forward direction and resisting this forward direction respectively. Also, the force of gravitational function pulls the particles of air in the direction of origin, and the Coriolis force's act to detect the particles of air in the atmosphere. To calculate the frictional, gravitational, pressure gradient force and Coriolis force, equations (3), (4), (5) and (6) are used, respectively. Which are given below [31].

$$F_{pg} = -\Delta\rho\sigma_v \quad (3)$$
$$F_c = -2\Omega \times \mu \quad (4)$$
$$F_g = -\rho\sigma_v \times g \quad (5)$$
$$F_f = -\rho\sigma_v \quad (6)$$

where Coriolis force; velocity factor of wind is represented by F_c. The Ω notation represents the earth rotation. The symbols F_f and α denotes friction force and friction coefficient respectively. F_{pg} is the gradient force due to pressure, δ_v represents the air finite volume, Δ denotes the gradient of pressure, F_g denotes the gravitational force, ρ and g is the density of air and acceleration because of gravitational force respectively. In WDO, particles of air are taken as n, and random solutions are formed from these particles. A fresh population is produced, after updating velocities and evaluating the fitness function. After this, the comparison of old and new air particles fitness function for an optimal home appliance scheduling structure is found.

D. BFO

BFO is a nature-stimulated optimization algorithm. It is inspired by the social searching behavior of Escherichia coli bacteria. In BFO algorithm, the bacteria swim in exploration of n number of nutrients and choose the best nutrients (solutions) to make the most of its energy. BFO also has four steps: reproduction, elimination-dispersal, swimming and chemotaxis. In the chemotaxis step, the parameters initialization of foraging starts, after that the parameters initialization takes place, the primary positions of all appliances are examined, and then the new positions of the bacteria (solution matrix) are calculated by the scheme. In the second step, the swimming loop is initialized to find the current best condition of the appliances, after this step is completed, the reproduction iteration loop starts. For the new population, only the fittest solution is used. Finally, the minimum fit solutions are removed, and new random samples are fitted with reduced probability. This is an important step because, the least fit solutions are rejected, and the probability of recurrence is minimized.

E. HGPDO

The HGPDO is our suggested algorithm. In HGPDO, the features of GA, BPSO and WDO algorithms are combined to proficiently reduce electricity bill cost, PAR and UC in terms of VC, TC and CO_2 emission. The GA, WDO and BPSO are chosen because these algorithms efficiently reduces PAR, effectively reduce electricity cost and return maximum UC in terms of visual and thermal comfort, respectively. HGPDO primarily has three stages where, in the stage one, the initial steps of PSO are implemented. In the stage two, the steps of WDO are adopted and in the third stage, the GA mutation and crossover are applied to the current global best position X_{gbest}^{t-1}, form by BPSO and $UC_{best}^{TC,VC}$ found by WDO, respectively. The GA features of crossover and mutation functioned at the best global position and best comfort offers good results as compared with their working to the individual and random based population. Figure 2 presents the flowchart of HGPDO algorithm. The parameters used in HGPDO and their values on which its best optimal results are achieved are listed in Table 2. All parameters and constraints values of GA, PSO and WDO are applied. The proposed method inputs, parameters initialization and step by step computation are given in Algorithm 1.

IV. SYSTEM MODEL

Consider a residential area, an EG connected smart home building (SHB) is fitted out with smart meters having load scheduling and energy storage system management controller (LSEMC) which employ and work on our proposed HGPDO algorithm. The LSEMC fetch all elements, such as electrical home appliances, user comfort signal (share preferences of appliances), renewable energy sources (RESs) local generations i.e., SE, WE, CHP running on biomass and energy storage devices i.e., home BSS and electric vehicle storage system (EVSS). Our algorithm will check for EV availability at home and having sufficient energy level to serve as backup at peak hours. Smart appliances will communicate with controller through home area network and LSEMC will control scheduling of those appliances on proposed scheme.

A LSEMC is operated at the external grid connected SHB which gathers these information: (i) UC signal about the loads pattern (i.e., scheduled or urgent; in terms of their durations of operations, tolerable delay, time of arrival, etc.) and comfort in terms of optical, heat, ventilation and air controller (HVAC), (ii) PV power generation output and corresponding constraints, (iii) Wind power generation

Algorithm 1: HGPDO Algorithm Steps

A. Algorithm Inputs: RTP, operation time duration, energy usage pattern, wind speed in m/s, temperature, solar irradiance, efficiency, bio-gas availability, prior-scheduling pattern of appliances, BSS, CHP and EVSS initialization.

B. Parameters initialization: Number of iterations, population size, P_m, P_c, N, W_i, C_1, C_2, dim_{min}, dim_{max}, V_{min}, V_{max}, R_t, n, g, a, maximum and minimum velocity, number of swarms, global and local pulls, initial and final momentum weights, cost per hour, PAR, T_c, V_c and emission of CO_2.

```
for Time = 1:24 do
    For initial position
    for hour = 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 vel1 = 1:10 do
        for vel2 = 1:6 do
            if Thour = 0 then
                H = 0
            end
        end
    end
    return V_best1, return P_best1
    For initial velocity and initial position, Calculate Vel_best1 and Pos_best1 Generate
      population for WDO
    Assign position and velocity
    begin
        Based on 1st position and velocity do evaluation of fitness function
        Using equations (1) and (2) update the velocity and position respectively
          Vel_best2, Pos_best2
        Based on 2nd best position and velocity do evaluation of fitness function
        Using equations (3)-(6) update velocity, position, check limits and boundaries,
          respectively
        Evaluate the fitness for WDO
        Check for T_c and V_c feasibility:
        if thermal comfort and visual comfort is less than WDO scheduled comfort then
            Crossover w_best and g_best, Crossover_result = crg
        end
        else
            Crossover Pos_best1 and Pos_best2, Crossover_result = crg, Mutate crg,
              Mutation_result = global_best
        end
    end
    returned global_best
    C. Compute objectives: EBC, PAR, Carbon emission and UC
    begin
        1. Compute user comfort
        for returned global_best, to calculate UC do
            a. Usage power schedule = global_best
            b. Compute TC using equations (29) and (43)
            c. Compute VC using equations (39) and (41)
            d. Compute delay comfort using equation (38)
            e. Compute air quality comfort by equation (44)
        end
        2. Compute electricity cost
        for returned global_best, to calculate cost do
            a. Only EG: L_t = Power × global_best
            b. EG with RES: Lt(RES) = Load-Energy from RES
            c. EG with RES and BSS: Lt(RES and BSS) = Load-Energy procured
               from RES-BSS discharge
            d. Compute EBC by equation (13) for Case a, b and c
        end
        3. Compute CO2 emission
        for returned global-best, to calculate CO2 emission do
            a. Only EG: average cost excluding RES and BSS
            b. EG with RES: average cost including RES
            c. EG with RES and BSS: average cost including both RES and BSS
            d. Compute CO2 by equation (37) for Case a, b and c
        end
        4. Compute PAR
        for Operated returned global best, to calculate PAR do
            a. Only EG: L_t = Power × global_best
            b. EG and RES: Lt(RES) = Load- Procured energy by RES
            c. EG, RES and BSS: Lt(RES and BSS) = Load- Procured energy from
               RES-BSS discharge
            d. Compute PAR by equation (36) for Case a, b and c
        end
    end
end
```

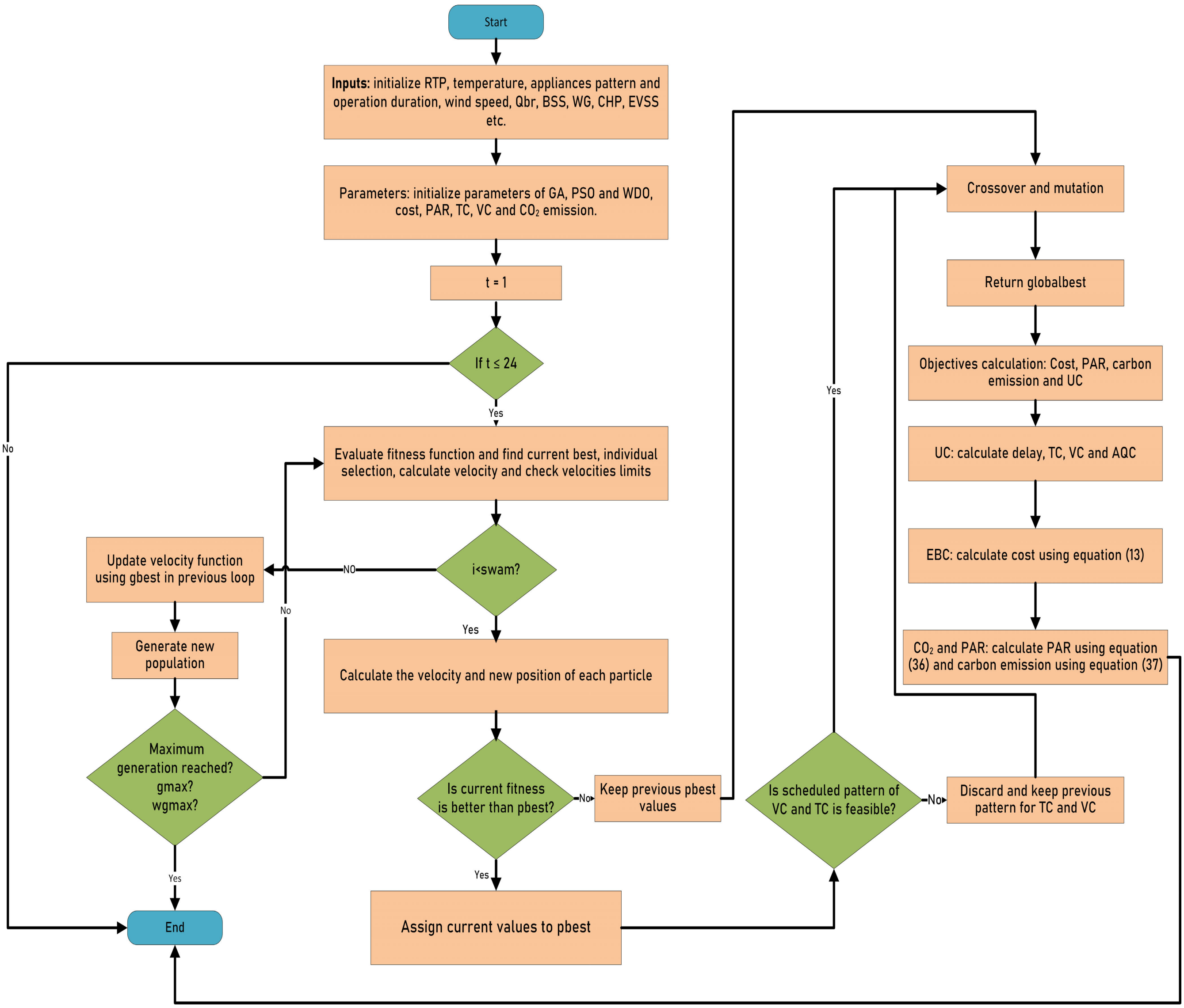

FIGURE 1. **Proposed HGPDO algorithm flowchart.**

output values and respective constraints, (iv) micro-combine heat and power (CHP) and gas boiler (GB) generation values and relevant constraints, (v) level of energy of both BSS and EVSS and their relevant constraints, (vi) real time price signals of electricity and external electricity grid constraints. On sharing the above information, the LSEMC apply the proposed algorithm to determine optimal scheduling, manage the energy and storage system. It is assumed that all the LSEMC operations are performed at fixed time slots, carried per time slot, and all the essential data is securely and timely brought by a communications network. There are many wireless solutions for communication purpose such as Wi-Fi, ZigBee, Z-Wave, or a wired home plug protocol in SG. A simple system architecture of SHB is presented in Figure 2.

A. ENERGY PROCUREMENT

The smart building in residential area procures energy for scheduled loads and urgent loads from EG, in home PV, WE and CHP. While in peak hours, it also uses BSS along with the EV battery as backup if available at home.

B. EXTERNAL GRID

The smart building is purchasing energy from external grid at defined price, discussed in subsequent subsection. The building procure energy from the external electricity grid. Let $E_{ex}(t)$, be the procured amount of energy from the grid at time t.

$$0 \leq E_{ex}(t) \leq E_{ex,max} \tag{7}$$

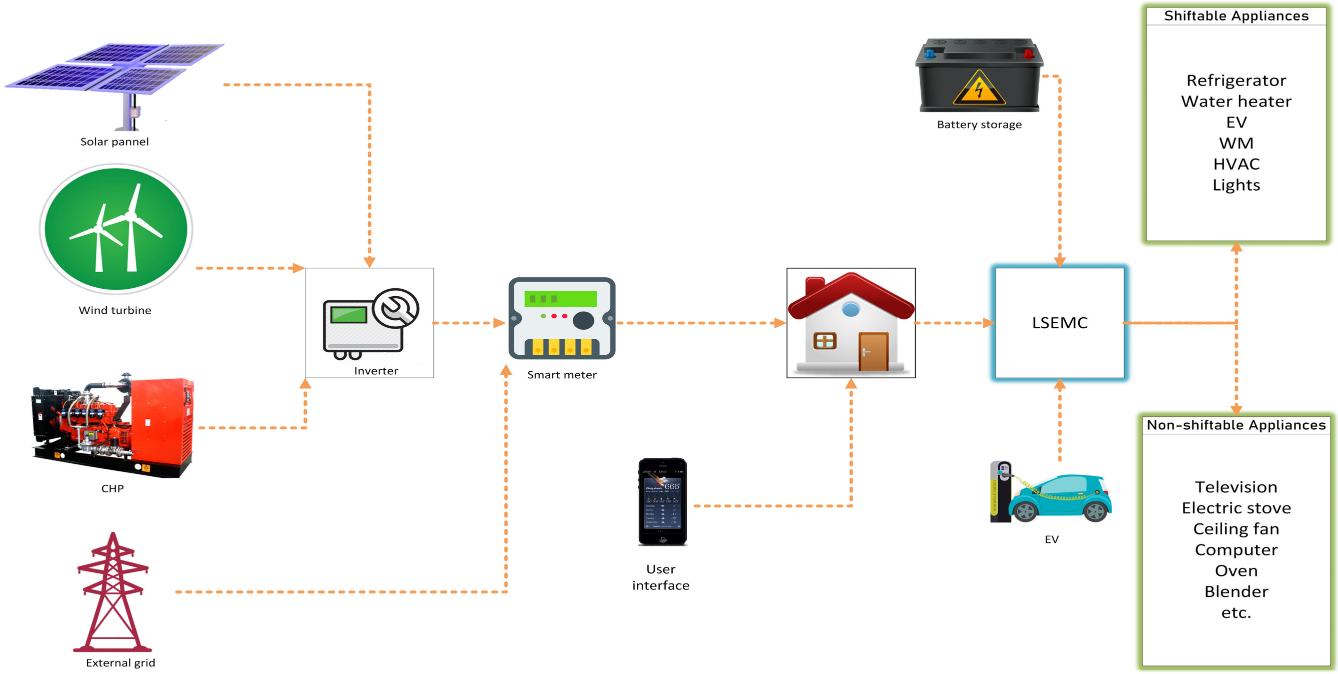

FIGURE 2. Proposed system model.

C. PRICE MODEL

There are several electricity tariffs, to set a price over 24 hours i.e., peak pricing (PP), time of use pricing (ToUP), critical peak pricing (CPP) and real time pricing (RTP) [31]. In most of the appliances scheduling systems, the pricing of electrical energy is supposed to be ToUP or RTP. Moreover, in ToUP, the pricing of total duration is divided into different slabs and for each slab a fixed price is defined. In this work, we practice RTP, in which the price of electrical energy vary on the hourly basis and rests constant during an hour's duration. Equations (8) and (9) calculate the 24 hours electricity bill of smart schedulable appliances (SSA) L^{sch} and non-schedulable appliances (NSA) L^{nsch} respectively.

$$L_{bill}^{sch} = \sum_{t=1}^{24} \left(\sum_{M=1}^{m} \left(L_{m\in M}^{sch}(t) \times S_{m\in M}^{sch}(t) \times EP(t) \right) \right) \tag{8}$$

$$L_{bill}^{nsch} = \sum_{t=1}^{24} \left(\sum_{N=1}^{n} \left(L_{n\in N}^{nsch}(t) \times S_{n\in N}^{nsch}(t) \times EP(t) \right) \right) \tag{9}$$

$$L_{bill}^{total} = L_{bill}^{sch} + L_{bill}^{nsch} = L_{bill}^{sch} = \sum_{t=1}^{24} \left(\sum_{M=1}^{m} \left(L_{m\in M}^{sch}(t) \times S_{m\in M}^{sch}(t) \times EP(t) \right) + \sum_{N=1}^{n} \left(L_{n\in N}^{nsch}(t) \times S_{n\in N}^{nsch}(t) \times EP(t) \right) \right) \tag{10}$$

$$S_{m\in M}^{sch}(t) = \begin{cases} 1 & \text{if schedulable appliance is ON} \\ 0 & \text{if schedulable appliance is OFF} \end{cases} \tag{11}$$

$$S_{m\in N}^{nsch}(t) = \begin{cases} 1 & \text{if non}-\text{schedulable appliance is ON} \\ 0 & \text{if non}-\text{schedulable appliance is OFF} \end{cases} \tag{12}$$

where $S_{m\in M}^{sch}(t)$ represent the indication of on/off state of M number SSA and $S_{n\in N}^{nsch}(t)$ represent the on/off state of N number NSA, and $EP(t)$ is electricity price in the particular time slot t. The electricity bill L at any time slot t after taking all RES and BSS into consideration is calculated as following

$$L_{bill} = (L^{sch}(t) + L^{nsch}(t) - (Eex(t) + E_{pv}(t) + P_{wd}(t) + E_{bio}(t)) - BSS(\tau)) \tag{13}$$

where the τ is the duration when the RESs are either not available or sufficient, so the load drains energy from BSS. Our main objective function is given in (14) below.

$$min\Big(\sum_{t=1}^{T} L_{bill}(t) + CO_2 + PAR + Delay\Big) \tag{14}$$

subject to constraints (15)-(19).

$$L^{sch}(t) + L^{nsch}(t) = (E(t) + BSS(t) + \varphi(t)) \tag{15}$$

$$\sum_{a=1}^{n} \eta = l(a) \tag{16}$$

$$\sum_{a=1}^{n} \alpha \leq \eta \leq \beta \tag{17}$$

$$\varphi(t) = RES \tag{18}$$

$$0 \leq BSS_{min} \leq BSS_{max}, \quad \forall t \in T \tag{19}$$

where, l represent length of appliance operation time, α and β shows the appliance operation start and end time respectively.

While, $\varphi(t)$ denotes the total procurement of renewable energies at time slot t.

D. PV GENERATION SYSTEM

PV panel solar power generation depend primarily on solar radiations and over-all estimated radiation [31]. Solar power output depend on radiation amount, direction of panels and transfer efficiency [33]. The generated energy in each time slot within 24 hours is firstly supplied to scheduled load and is characterized as in (20) [31].

$$E_{pv}(t) = E_{pv}\, A_{pv}\, Ir(t)\, (1 - 0.05)\, (T_a(t) - 25) \quad \forall\, t \tag{20}$$

In equation (20), E_{pv} denotes the energy efficiency conversion factor of the solar panels, A_{pv} is the surface area of the panels (m^2), $Ir(t)$ is the radiance of solar (kW/m^2) at time t, the correction factor of temperature is 0.005 [34], $T_a(t)$ denotes the outside temperature in (°C) at time t and standard room temperature is 25(°C). The sun hourly irradiation distribution generally follows a bimodal spreading that can be measured as a linear blend of two unimodal distribution functions. It could be demonstrated using Weibull probability density function as in equation (21) [33].

$$\begin{aligned} f\left(Ir_{pv}(t)\right) = \zeta \left(\frac{\alpha 1}{\beta 1}\right)\left(\frac{Ir(t)}{\beta 1}\right)^{(\alpha 1-1)} e^{-\left(\frac{Ir}{\beta 1}\right)^{\alpha 1}} + (1-\zeta) \\ \times \left(\frac{\alpha 2}{\beta 2}\right)\left(\frac{Ir(t)}{\beta 2}\right)^{(\alpha 2-1)} e^{-\left(\frac{Ir_{pv}}{\beta 1}\right)^{\alpha 2}} \\ 0 < Ir(t) < \infty \end{aligned} \tag{21}$$

where, ζ denotes a weighted factor, α_1 and α_2 are the shape factors, together with β_1 and $\beta_2$which are scale factors.

E. WIND ENERGY

Power generation of wind turbines owed to the kinematic energy of wind speed, hence, its production of electrical energy primarily depends on meteorological conditions and direction of wind flow. It is assumed that procured amount of energy from wind turbine is given by:

$$P_{wd}(t) = \frac{1}{2} * \rho * A_{tb} * V_s(t)^3 \tag{22}$$

where, ρ, A_{tb} denotes the air density and area of turbine blade, respectively, while, the symbol $V_s(t)$ denotes the air speed in m/s.

F. MICRO-CHP

In order to meet the SHB power demand, it is supposed that the building is acquiring energy from its own controllable micro-CHP generation system. Details of CHP system are specified as follows. CHP system electricity generation on average uses 32% less fuel, thus results in 50% less carbon emission. Renewable fuel such as biomass, biogas, renewable natural gas (RNG) and renewable hydrogen (RH) have potential to reduce carbon emission even further. For thermal generation, electrical generation or as transport fuel, the methane CH_4 biogas can be used [5]. The efficiency CHP system is calculated by equation 23:

$$\partial = \frac{W_e + \sum Q_{th}}{Q_f} \tag{23}$$

In the above equation symbol ∂ is the total system efficiency, W_e is the valuable electric output, Q_{th} is the total thermal output and Q_f is the fuel energy input. A CHP system achieve about 60 to 80 percent efficiency.

The important fuel source for CHP is biomass, mostly produced from the forests. From the decomposition of organic matter the biogas is obtained in the absence of oxygen in a controlled tanks or landfills. CH_4 is the main components of biogas. CH_4 concentration generally ranges from 30% to 65%. CH_4 material of biogas can be used for thermal and electrical power generation as a transport fuel. Now, biogas is an active means for producing RE, so it in turn plays a significant part in energy production and is eco-friendly. There are numerous means for gaining biogas in the urban areas like waste of Industries, pruning waste, solid waste, municipal and industrial wastewater. The electrical power generation through biogas is defined in equation (24). This equation is associated to the biogas conversion to valuable energy of heat and electricity [5].

$$E_{bio}(t) = \frac{L * Q_{br}(t) * \partial}{\gamma_e} \tag{24}$$

where $E_{bio}(t)$ is the available electrical power (kWh) at slot t, L is lower biogas calorific value, Q_{br} is biogas recovery and availability, ∂ is efficiency and γ_e is recovery efficiency. The total power P of micro-CHP generator is calculated using equation (25) as in [5]. Where CF denote capacity factor; is the plant accessibility factor which is taken in [80-90]% and t is duration in hours.

$$P(t) = \frac{E_{bio}(t)}{t * CF} \tag{25}$$

G. EV ON BOARD PV

EV On board PV generated energy is used for driving tasks and remaining is stored in electric vehicle storage system (EVSS). We assume that the harvested amount of energy from the PV source installed at EV is firstly used for driving loads and motor [13], while, the remaining energy is stored in EVSS. The EV on-board PV harvested amount of energy is g_t, such that:

$$p_t = min\left\{\sum_{\tau=0}^{t} lm_\tau 1_\tau(\Delta_\omega, \tau), g_t\right\} \tag{26}$$

where, the term $\sum_{\tau=0}^{t} lm_\tau 1_\tau(\Delta_\omega, \tau)$ represents the total EV load arriving at time slot t [13]. The $1_\tau(\Delta_\omega, \tau)$ indicate whether the load lm_τ is being served or not at time slot τ. The remaining energy, if any, is stored into EVSS and drawn from it only in peak hours and if the home BSS is not sufficient.

H. POWER CONSUMPTION

In SHB there are schedulable smart appliances and fixed appliances which consume power from EG and RES. Power consumption of load and HVAC is discussed below in detail.

I. LOAD CONSUMPTION MODEL

We suppose that SHB has different appliances loads $L(t)$ at 24 hour duration which arrive over the time slots with temporal variability and uncertainty. Each $L(t)$ has power rating ς for a duration. In this work, the appliances are classified in two kinds: smart schedulable appliances (SSA). SSA can operate themselves such as washing machines, dish washer, air conditioners, refrigerator and manually-operated [12] while fixed loads does not incur in bill or PAR reduction. Consider that the SH has two major sets of appliances i.e. L^{sch} and L^{nsch}, where L^{sch} is the set of schedulable i.e., can be shifted to operate in low peak slots, $L^{sch}(t) = \{a_1, a_2, a_3 \ldots a_m\}$ and L^{nsch} is the set of non-schedulable appliances i.e., immediately operate on the time and preference set by the consumer, $L^{nsch}(t) = \{b_1, b_2, b_3 \ldots b_n\}$ over a scheduling duration of $t = \{1, 2, 3, \ldots, 24\}$. The 24 hours energy consumption of schedulable and non-schedulable load are given by equations (27) and (28) respectively.

$$L^{sch}(t) = \sum_{t=1}^{24}\left(\sum_{M=1}^{m} L^{sch}t, m \in M\right) = \{L^{sch}t1, m \in M + L^{sch}t2, m \in M + \ldots + L^{sch}t24, m \in M\} \tag{27}$$

$$L^{nsch}(t) = \sum_{t=1}^{24}\left(\sum_{M=1}^{m} L^{sch}t, m \in M\right) = \{L^{nsch}t1, m \in M + L^{nsch}t2, m \in M + \ldots + L^{nsch}t24, m \in M\} \tag{28}$$

J. HVAC CONSUMPTION MODEL

HVAC is other shift-able appliance for heating, cooling and ventilation in a building. HVAC uses almost 50% of total consumption [25]. The HVAC generally, has two mode of operations i.e., heating and air cooling. In this work, we focused on cooling in summer and heating in winter. According to [25], the indoor temperature dynamics caused by an HVAC system could be obtained as follows:

$$T_{t+1} = \epsilon T_t + (1 - \epsilon)(T_t^{out} + \frac{\eta_e}{A_c} e_t), \quad \forall\, t \tag{29}$$

where, T_t the indoor temperature and T_t^{out} denote outdoor temperature, η_e is the thermal conversion efficiency, and A_c in $kW/°F$ is the overall thermal conductivity, moreover, $\varepsilon = e^{-\tau/\omega}$ where ω is the time constant of system.

K. STORAGE MODEL

1) BSS MODEL

BSS is used to stores the remaining amount of RE to serve as backup in peak hours. It stores the energy by satisfying the overcharging and depth of charging constraints. Energy charged in the BSS at time slot t is described by equation (30) as in [31]. The electricity discharged, the electricity charged and the self-discharging rate is also considered. The discharging and charging of BSS would gain or lose electrical energy, so turn-around the BSS efficiency is depicted as:

$$BS(t) = BS(t - 1) + k.\delta^{BS}.EP^{ch}(t) - \frac{k.EP^{dch}(t)}{\delta^{BS}} \tag{30}$$

where, BS denote the stored energy (Ah) at time t, k is time slot duration (hour), δ^{BS} is the efficiency of BSS, EP^{ch} is the electric power (kW) provided to BSS from RES at time t and EP^{dch} is the electric power (kW) provided to the load from BSS at time t. The battery charging and discharging constraints are given below.

$$EP^{ch}(t) \le EP_{UB}^{ch} \tag{31}$$
$$EP^{dch}(t) \le EP_{LB}^{dch} \tag{32}$$
$$BSS(t) \le ES_{UB}^{ch} \tag{33}$$

In order to keep the BSS in good condition and avoid deep discharging or overcharging, discharge and charge rate of electrical energy, and energy stored in BSS should not cross the limits approved by the company.

2) EVSS MOBILE BACKUP

Depending on the EV total load and total source conditions, the EVSS can be charged from PV, WE system and external power grid and its on-board PV [13]. EVSS can be used as a mobile backup, our algorithm will check for the availability of EV at home and the battery charge level for serving as mobile backup in peak hours to shift load. Let EV availability is indicated as:

$$Ev(a) = \{1 \text{ if availabe at home, else } 0\} \tag{34}$$

$$Ev(s) = \{1 \text{ if charging, } 0 \text{ idle and } -1 \text{ if discharging}\} \tag{35}$$

The EV battery charging level at different hours after the driving tasks and status of availability is shown in Figure 12 and charge level in Figure 13.

L. PAR

PAR is the ratio of peak load consumed in a time slot t and the average of total load used over the scheduling hours duration i.e., from $t = 1$ to T where $T = 24$ hours. PAR describes the power consumption activities of the user and the operation EG peak hours and have a direct relationship with the user PARs. So, it is in favor for both the electric utility and user to mitigate PAR so that energy supply and user demand balance can be sustained. For single user, it is considered as in [33].

$$PAR = \frac{max(L^{total}(t))}{\frac{1}{T}\sum_{t=1}^{T} L^{total}(t)} \tag{36}$$

M. CARBON EMISSION

In this work, carbon emission is calculated using equation (37) as in [31] and [14]. Where $avg(EP(t))$ denotes the average cost of electricity per month, while η illustrate the electricity price per kWh equal to 0.20 dollars and γ represents the emission factor of electricity equal to 1.37, while m denotes number of months in one year.

$$CO_2 = \frac{avg(EP(t))}{\eta.\gamma.m} \tag{37}$$

N. UC MODEL

In this work, we compute the UC in terms of delay, thermal, air quality and visual comfort, each details and mathematical formulation is given below.

1) DELAY COMFORT

This comfort is related to serving time of each appliance. Delay comfort is calculated using equation (38) as in [31]. Where $unsch(t)$ denotes the time of serving in unscheduled method while $sch(t)$ denotes the time of serving in scheduled method. Delay and electricity cost are both related to UC.

$$D_{comfort} = \frac{\sum |unsch\ (t) - sch\ (t)|}{\sum (sch\ (t))} \tag{38}$$

2) VISUAL COMFORT

Visual comfort is related to the number of lights and waiting time to serve. It will be adjusted to user preference while, indoor luminous intensity is defined as in [14].

$$V_{comfort}(t) \triangleq \frac{Ne.Le\,(t)\ .fs\,.\,\vartheta.M}{A} \tag{39}$$

where N_e denotes the number of lightening devices, $V_{comfort}(t)$ in (39) shows the indoor illumination in A illuminated indoor area. The room luminous can be adjusted by energy consumption level of individual lighting devices $L_e(t)$, that have their respective source flux value f_s, ϑ utilization factor and M maintenance factor. The user visual comfort V_c and delay $AP_{W_t}^{Lights}$ have an inverse relation, this relationship can be mathematically presented as in [29]:

$$V_c \propto \frac{1}{AP_{W_t}^{Lights}} \tag{40}$$

$$AP_{W_t}^{Lights} = (AP_{D_h}^{Lights} - AP_{S_h}^{Lights}) \tag{41}$$

where $AP_{D_h}^{Lights}$ is the user preference of lights and $AP_{S_h}^{Lights}$ is the scheduled hours for lights.

3) INDOOR TEMPERATURE COMFORT

The temperature of adjustable HVAC system, their temperature is varied in a definite range which is based on user preferences. The indoor temperature can be adjusted by varying the energy consumption of temperature adjustable HVAC equipment. The indoor temperature is varied within the range of 20°C $\sim$ 25°C [14], for a single person in the smart home, to feel comfortable. The thermal comfort is calculated by equation (43). The user thermal comfort and waiting time $AP_{W_t}^{HVAC}$ have an inverse relation, this relationship can be mathematically expressed as follows:

$$T_c \propto \frac{1}{AP_{W_t}^{HVAC}} \tag{42}$$

$$AP_{W_t}^{HVAC} = (AP_{D_h}^{HVAC} - AP_{S_h}^{HVAC}) \tag{43}$$

where T_c is the thermal comfort, $AP_{D_h}^{HVAC}$ is user preference of HVAC and $AP_{S_h}^{HVAC}$ is the scheduled hours for HVAC.

4) AIR QUALITY

Air quality is measured in terms of carbon emission in the environment. The concentration of indoor carbon can be varied through adaptive ventilation system in the SHB. Thus, based on user preferences, indoor good air quality can be kept by ventilating fresh air into the indoor area. Mathematically, the parameters of the indoor carbon concentration can be stated as in [14]:

$$\zeta_{t+1} = \zeta_t + \frac{F_{air}(\zeta_{out} - \zeta_t) + \zeta_{in}}{V} \tag{44}$$

This equation (44) shows that the carbon concentration ζ_{t+1} in an indoor zone of volume V that can be adjusted by varying the amount of fresh air F_{air} in the zone with respect to its accumulation value of the CO_2 concentration ζ_t depending upon the outdoor carbon concentration ζ_{out} and the indoor carbon generation ζ_{in}. The fresh air cooling and heating can be adjusted by complementing the equation (29) when the cooling mode is required. The desired range of indoor fresh air is taken in terms of carbon concentration which ranges between 740ppm $\sim$ 780ppm [14].

V. RESULTS AND DISCUSSION

The results and simulations of proposed LSEMC algorithm are presented in this section. In our system model, the incorporation of RES, BSS, EVSS and proposed HGPDO algorithm performance is evaluated and discussed in three cases. In case one, only EG (excluding RES and BSS), while, the case two is EG with RES, and the case three is EG combine with both BSS and RES. For simulations, we used the MATLAB simulation tool. To discuss the suggested LSEMC, we assumed a smart home having six shiftable appliances and EG, RES and BSS as a source. While BSS and EVSS is only used at peak price hours for load shifting. The smart grid signals; RTP [31], forecasted temperature [4], wind speed [4], biogas output [5] and solar irradiance [33] taken in the suggested LSEMC are showed in Figures 3, 4, 5, 6 and 7 respectively. The electricity generation by solar system primarily depends on ambient temperature and solar irradiance, while, wind and CHP depends on wind speed and biogas recovery efficiency. We have assumed 90% of total RES in all available time slots of the scheduled time. As well, 30% of RES in each time slot is consumed for BSS charging, of which the 20% contributes from the solar, while 10% contributes from the wind and CHP. Figure 8, 9 and 10 shows the estimated power generation of solar, CHP, wind and the remaining RE after BSS charging respectively. Furthermore, figure 11 shows charging level of BSS along with EVSS.

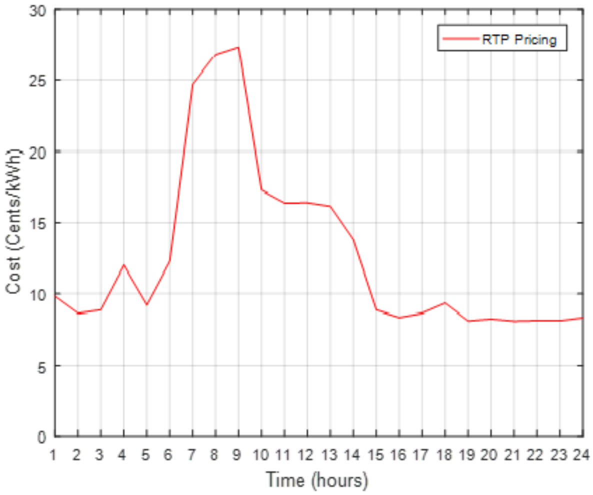

FIGURE 3. Real time pricing signal.

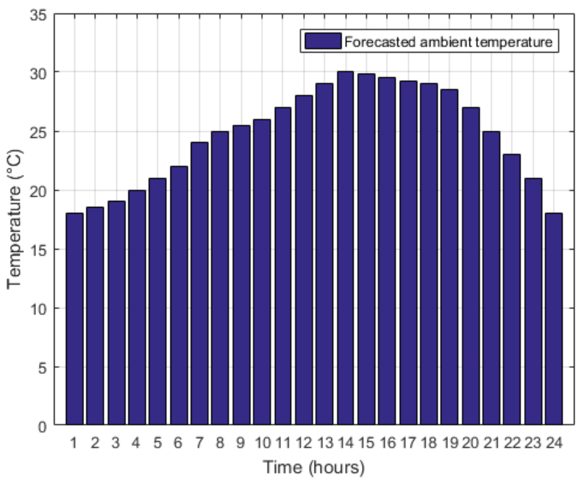

FIGURE 4. Forecasted temperature.

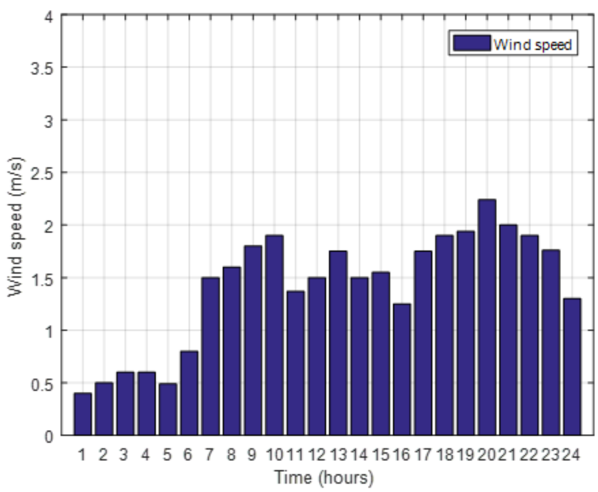

FIGURE 5. Forecasted wind speed.

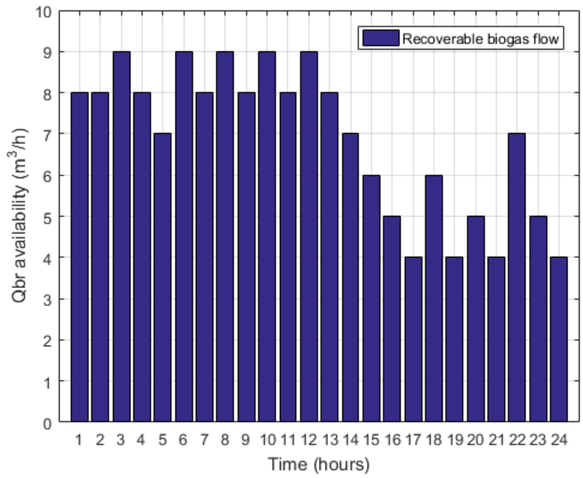

FIGURE 6. Biogas Qbr availability.

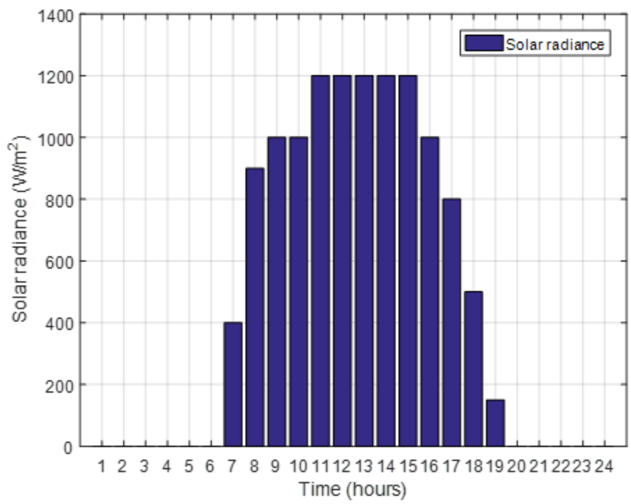

FIGURE 7. Solar irradiance.

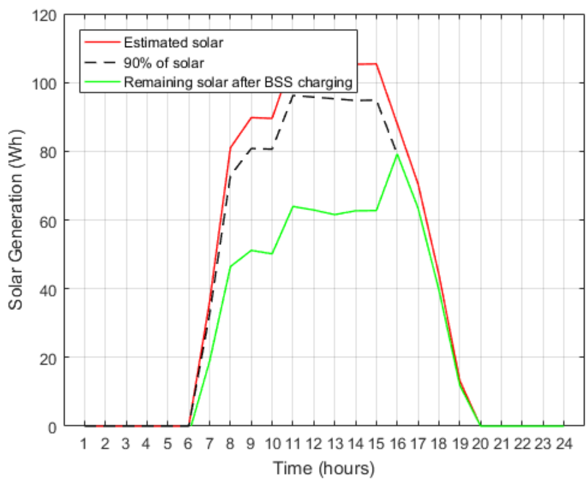

FIGURE 8. Solar power generation.

A. CASE 1: ONLY EG

In this scenario, the smart home building is only using the external grid power for scheduled and unscheduled loads. We will discuss electricity bill cost (EBC), PAR and carbon emission.

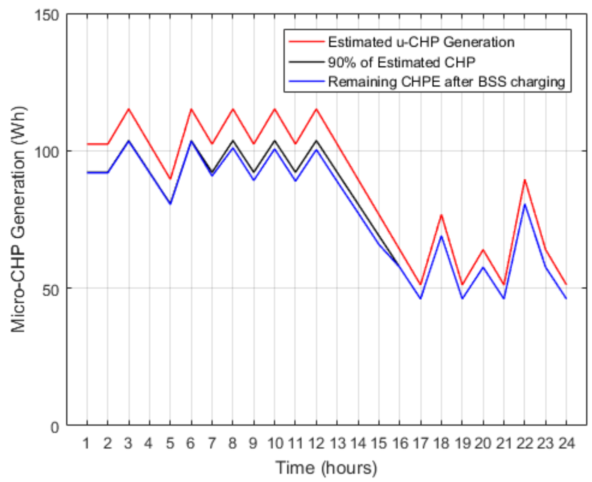

FIGURE 9. CHP power generation.

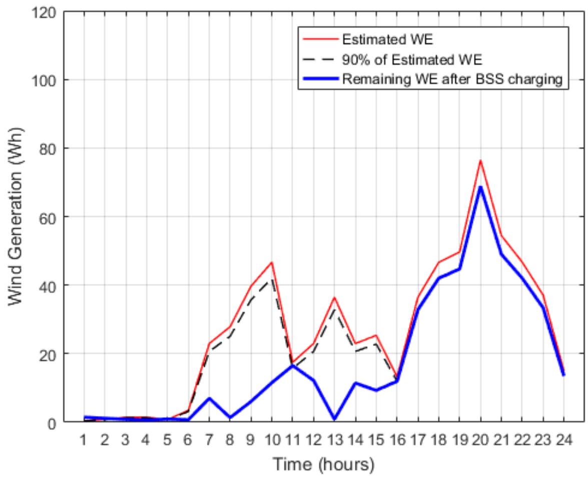

FIGURE 10. Wind power generation.

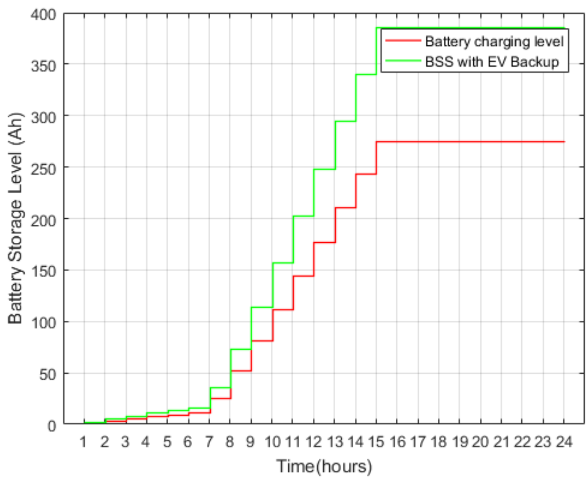

FIGURE 11. BSS and EVSS charging.

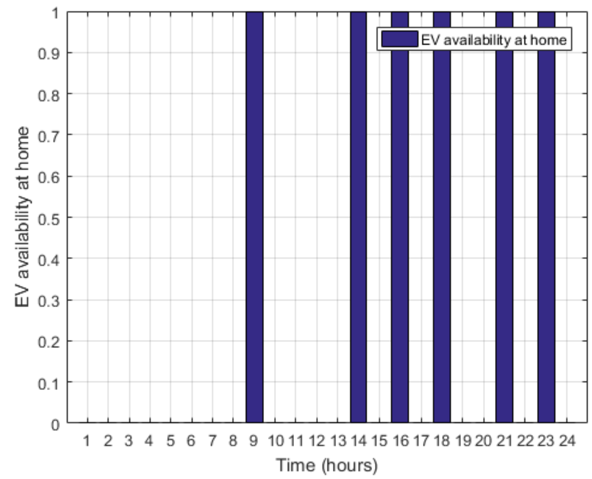

FIGURE 12. EV availability at home.

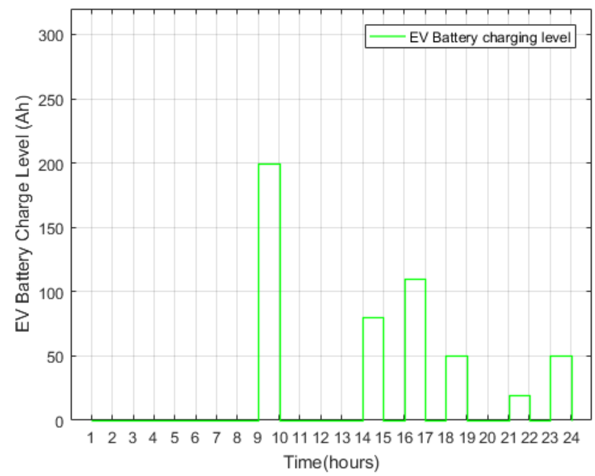

FIGURE 13. EVSS Charge level at different slots.

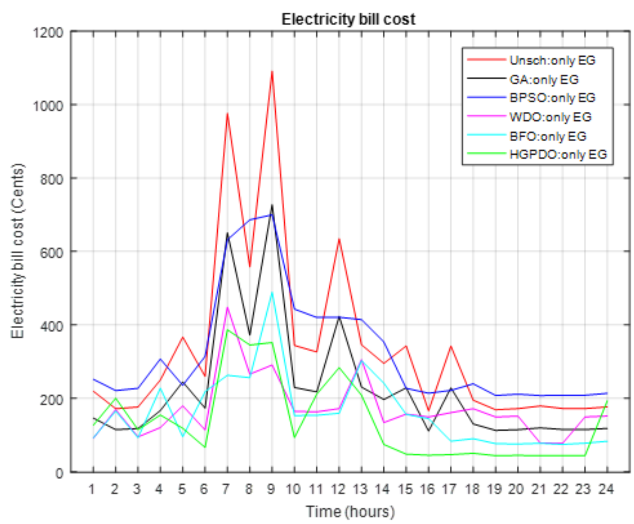

FIGURE 14. Case 1 electricity bill cost.

1) ELECTRICITY BILL COST

Figure 14 demonstrates the EBC of unscheduled load and scheduled load without BSS and RESs. In unscheduled, the maximum electricity cost is 1091 cents in slot hour 9 and in hour slot 16, the minimum cost is 165.81 cents. In case of BPSO, the maximum electricity cost is 727.41 cents in the hour slot 9 and minimum cost is at hour slot 19.

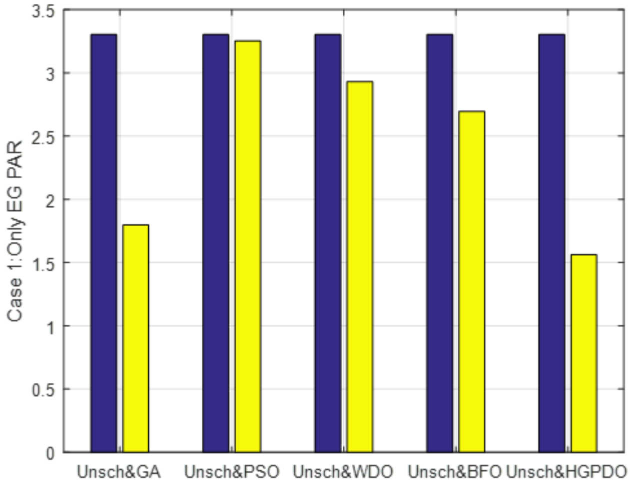

FIGURE 15. Case 1 PAR.

In case of WDO, the maximum electricity cost is 699.70 cents in the hour slot 9. In HGPDO algorithm, maximum cost in the hour slot 7 is 386.64 cents, whereas in BFO, it is 488.83 cents in time hour slot 9. It is 727.41 cents in the time slot 9 in GA based scheduling method. The HGPDO algorithm performance is better in terms of EBC reduction when compared with the other exploratory algorithms. The average electricity bill over 24 hours in unscheduled, GA, WDO, BPSO and BFO are 337.34, 224.89, 170.92, 324.17, 160.07 cents, respectively. While with our proposed algorithm, it is 138.82 cents. The cumulative, electricity bill cost illustrates that GA, BPSO, WDO, BFO and HGPDO reduce the electricity bill cost by 33.33%, 3.90%, 49.33%, 52.54% and 58.69%, respectively. Nevertheless, in this case, the best cost minimization is achieved with the proposed scheduling algorithm. The average cost over 24 hours of all algorithms as compared with the proposed model is shown in Table 3.

TABLE 3. Case 1 cost comparison.

Algorithm	Average cost (cents)	Difference (average cents)	Reduction (%)
Unscheduled	337.34	- -	- -
GA	224.89	112.45	33.33%
BPSO	324.17	13.17	3.90%
WDO	170.92	166.42	49.33%
BFO	160.07	177.27	52.54%
HGPDO	138.82	198.52	58.69%

2) PAR

Figure 15 shows the PAR in Case 1, when SHB is only utilizing energy from EG. In unscheduled it is 3.302, while in GA, PSO, WDO and HGPDO it is 3.037, 2.964, 2.836, 2.654 and 1.559 respectively. Results demonstrate that GA, PSO, WDO, BFO and HGPDO reduce the PAR by 8.025%, 10.23%, 14.11%, 19.62% and 52.78% respectively. Although the PSO and WDO shift load to low peak price hours which create new peaks and disturb the utility system. A penalty is required to be imposed for preventing the system from such disturbance. Table 4 shows the PAR comparison of all algorithms with the proposed algorithm for the Case 1.

TABLE 4. Case 1 PAR comparison.

Algorithm	Total PAR	Difference (PAR)	Reduction (%)
Unscheduled	3.302	- -	- -
GA	3.037	0.265	8.025%
BPSO	2.964	0.338	10.23%
WDO	2.836	0.466	14.11%
BFO	2.654	0.648	19.62%
HGPDO	1.559	1.743	52.78%

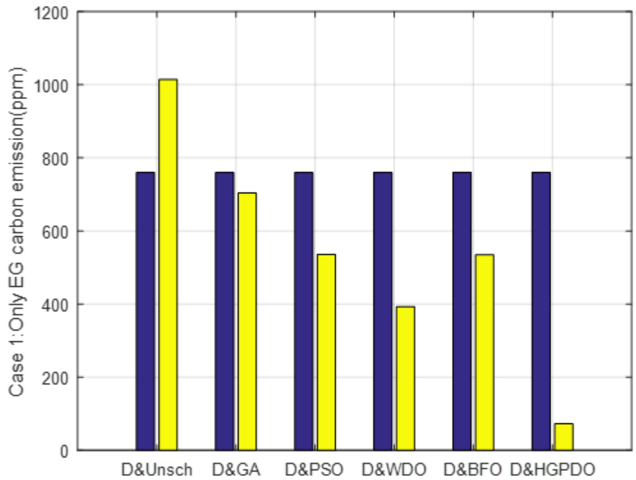

FIGURE 16. Case 1 carbon emission in (ppm).

3) CARBON EMISSION

Carbon emission in Case 1 is shown in Figure 16. Where the desired carbon (D) is 760ppm. In case of unscheduled it is 1014 ppm, which shows carbon emission is far from the desired range. While in GA, BPSO, WDO, BFO and HGPDO it is 703.7 ppm, 535.5 ppm, 393.1 ppm 534.8 ppm and 72.4 ppm respectively. The reduction in carbon emission in this case for GA, BPSO, WDO, BFO and HGPDO is 7.40%, 29.53%, 48.27%, 29.63% and 72.40% respectively. In this case, WDO and HGPDO show good results in case of carbon emission reduction. Table 5 illustrate the comparisons of user desired, unscheduled carbon emission and emission by all scheduling algorithms.

TABLE 5. Case 1 carbon emission comparison.

Algorithm	Carbon emission (ppm)	Difference (ppm)	Reduction (%)
CO_2 concentration	760	- -	- -
Unscheduled	1014.0	-254	-33.42% (increased)
GA	703.7	56.30	7.40%
BPSO	535.5	224.5	29.53%
WDO	393.1	336.9	48.27%
BFO	534.8	225.2	29.63%
HGPDO	72.4	687.6	72.40%

B. CASE 2: EG WITH RES INTEGRATION

In this scenario, the smart building is using the external grid power along with RES for scheduled and unscheduled task. We will discuss EBC, PAR and carbon emission.

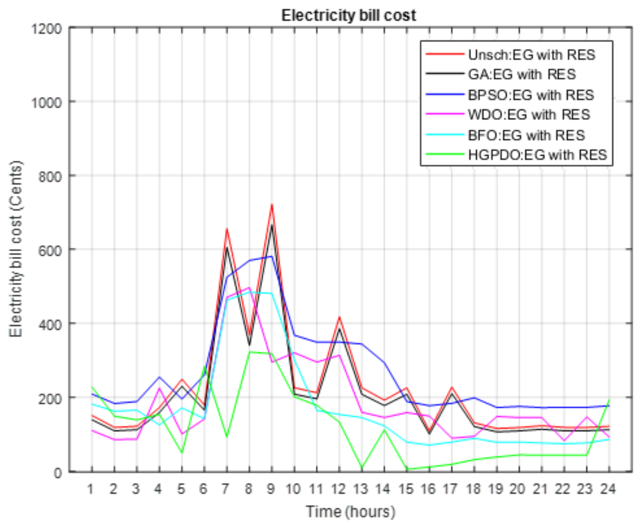

FIGURE 17. Case 2 electricity bill cost.

1) ELECTRICITY BILL COST

Figure 17 demonstrates the EBC of unscheduled load and scheduled load utilizing power from EG and RES. In unscheduled, the maximum electricity cost is 722.35 cents in slot hour 9 and in slot hour 16, the minimum cost is 109.10 cents. In BPSO, the maximum cost is 581.13 cents in the hour slot 9 and minimum cost is at hour slot 19. In case of WDO, the maximum electricity cost is 496.55 cents in the slot hour 9. In HGPDO algorithm, cost is 322.24 cents in the slot hour 8, while in BFO, it is 484.37 cents at slot hour 9. In GA centered scheduling method, cost is 666.79 cents in slot hour 9. The performance of the HGPDO algorithm in terms of EBC reduction is better when compared with the other discussed exploratory algorithms. The average electricity bill over 24 hours in unscheduled method, GA, BPSO, WDO and BFO are 225.91, 208.53, 216.23, 187.45 and 168.82 cents, respectively. While with our proposed algorithm it is 118.48 cents. In cumulative, electricity bill cost illustrate that GA, BPSO, WDO, BFO and HGPDO reduce the electricity bill cost by 7.69%, 4.21%, 17.02%, 22.27% and 47.55%, respectively. Nevertheless, in this Case 2 the best cost minimization is achieved with the proposed scheduling algorithm. The average cost over 24 hours duration comparison of all algorithms and the proposed algorithm in case two is shown in Table 6.

TABLE 6. Case 2 cost comparison.

Algorithm	Average cost (cents)	Difference (average cents)	Reduction (%)
Unscheduled	225.91	–	–
GA	208.53	17.38	7.69%
BPSO	216.23	9.68	4.21%
WDO	187.45	38.46	17.02%
BFO	168.82	57.09	25.27%
HGPDO	118.48	107.43	47.55%

2) PAR

Figure 18 shows the PAR in Case 2, when SHB is utilizing energy from EG and RESs. In unscheduled, it is 2.985, while in the case of GA, PSO, WDO, BFO and HGPDO it is 2.803, 2.523, 2.453, 2.185 and 1.651 respectively. The results demonstrate that GA, PSO, WDO, BFO and HGPDO reduce the PAR by 6.13%, 15.47%, 17.82%, 26.80% and 45.02% respectively. BFO and our proposed algorithm reduce PAR very efficiently. Although the PSO and WDO shift load to low peak price hours which create new peaks and disturb the utility system. A penalty is required to be imposed for preventing the system from such disturbance. Table 7 shows the PAR comparisons of all algorithms with the proposed algorithm for the Case 2.

TABLE 7. Case 2 PAR comparison.

Algorithm	Total PAR	Difference (PAR)	Reduction (%)
Unscheduled	2.985	- -	- -
GA	2.803	0.183	6.13%
BPSO	2.523	0.462	15.47%
WDO	2.453	0.532	17.82%
BFO	2.185	0.800	26.80%
HGPDO	1.651	1.344	45.02%

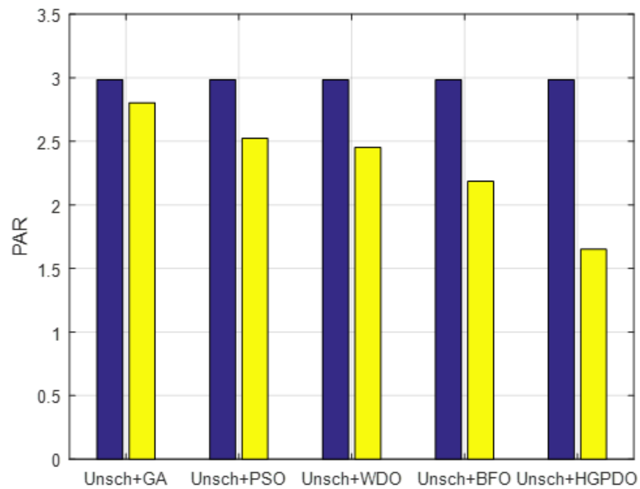

FIGURE 18. Case 2 PAR.

3) CARBON EMISSION

Carbon emission in Case 2 is shown in Figure 19. Where the desired carbon (D) is 760ppm. In case of unscheduled, it is 1003 ppm, which shows carbon emission is far from the desired range. While in GA, BPSO, WDO, BFO and HGPDO it is 682.1 ppm, 446.8 ppm, 360.7 ppm 594 ppm and 53.4 ppm, respectively. The reduction of carbon emission in this case for GA, BPSO, WDO, BFO and HGPDO is 10.50%, 41.21%, 52.60%, 21.84% and 92.90% respectively. In this case, WDO and HGPDO shows good results in terms of carbon emission reduction. Table 8 illustrate the comparison of desired, unscheduled carbon emission and emission by all scheduling algorithms.

C. CASE 3: EG WITH RES AND BSS INTEGRATION

In this scenario, the smart building using the external grid power for scheduled and unscheduled task along with RES

TABLE 8. Case 2 carbon emission comparison.

Algorithm	Carbon emission (ppm)	Difference (ppm)	Reduction (%)
CO_2 concentration	760	- -	- -
Unscheduled	1003	-243	-31.97%(increased)
GA	682.1	77.9	10.50%
BPSO	446.8	313.2	41.21%
WDO	360.7	399.8	52.60%
BFO	594	166	21.84%
HGPDO	53.4	706.6	92.90%

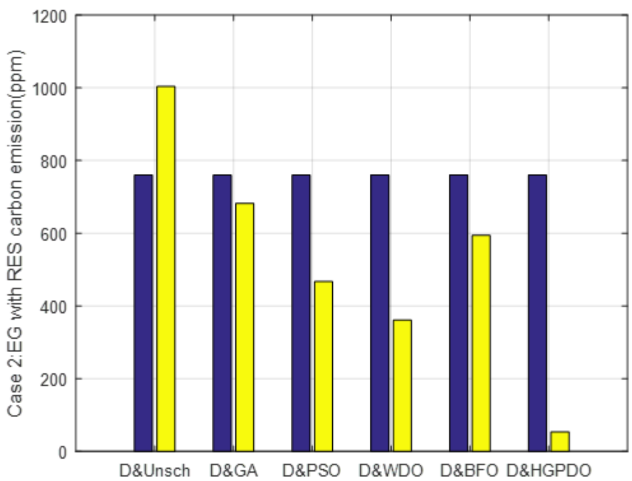

FIGURE 19. Case 2 carbon emission in (ppm).

TABLE 9. Case 3 cost comparison.

Algorithm	Average cost (cents)	Difference (average cents)	Reduction (%)
Unscheduled	222.51	- -	- -
GA	203.97	21.54	9.68%
BPSO	213.30	9.21	4.13%
WDO	175.05	47.46	21.32%
BFO	156.38	66.13	29.72%
HGPDO	147.61	74.9	33.66%

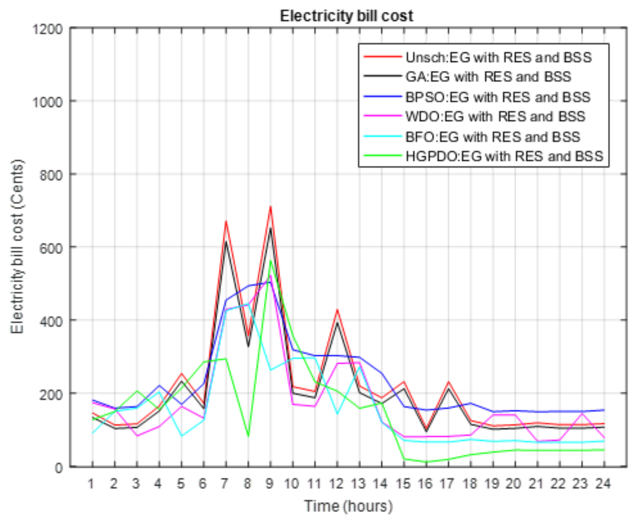

FIGURE 20. Case 3 electricity bill cost.

and BSS and EVSS. We will discuss EBC, PAR, carbon emission and UC.

1) ELECTRICITY BILL COST

Figure 20 demonstrates the EBC of unscheduled load and scheduled load, utilizing power from EG with RES and BSS. In unscheduled, the maximum electricity cost is 711.82 cents in slot hour 9 and minimum cost is 102.88 cents in slot hour 16. In BPSO, the maximum electricity cost is 503.57 cents in the slot hour 9 and minimum cost is at slot hour 19. In WDO, the maximum cost of electricity is 522.29 cents in the slot hour 9. In HGPDO algorithm, cost is 423.48 cents in the slot hour 8, while in BFO, it is 444.97 cents in slot hour 9. In case of GA based scheduling technique, it is 652.51 cents in the slot hour 9. The HGPDO algorithm performance is better in terms of EBC reduction when compared with the other discussed algorithms. The average electricity bill over 24 hours in unscheduled, GA, BPSO, WDO and BFO are 222.51, 203.97, 213.30, 175.05 and 156.38 cents, respectively. While with our proposed algorithm it is 147.61 cents. The cumulative, electricity bill cost illustrates that GA, BPSO, WDO, BFO and HGPDO reduces the electricity bill cost by 9.68%, 4.13%, 21.32%, 29.72% and 33.66%, respectively. Nevertheless, in this Case 3 the best cost minimization is achieved with proposed scheduling algorithm which uniformly distribute load over low and high peaks hours. The average cost over 24 hours duration comparison of all algorithms and proposed algorithm in Case 3 is shown in Table 9.

2) PAR

Figure 21 demonstrates the PAR of user scheduled and unscheduled load. In unscheduled, it is 2.537, while in the case of GA, PSO, WDO, BFO and HGPDO it is 2.197, 2.049, 1.741, 1.727 and 1.158 respectively. The results demonstrate that the PAR is reduced as a result of proposed GA, PSO, WDO, BFO and HGPDO algorithms by 13.40%, 19.23%, 31.37%, 31.92% and 54.35%, respectively. Nevertheless, the HGPDO algorithm curtail the PAR significantly as compared with the other exploratory algorithms. The load is shifted to off peak slots by GA and WDO and create new peaks. Conversely, the PSO and HGPDO algorithms allocate the load equally and attain the required objective. Table 10 present the PAR comparisons of all algorithms with the proposed algorithm in the Case 3.

TABLE 10. Case 3 PAR comparison.

Algorithm	Total PAR	Difference (PAR)	Reduction(%)
Unscheduled	2.537	- -	- -
GA	2.197	0.340	13.40%
BPSO	2.049	0.488	19.23%
WDO	1.741	0.796	31.37%
BFO	1.727	0.810	31.92%
HGPDO	1.158	1.379	54.35%

3) CARBON EMISSION

Carbon emission in Case 3 is shown in Figure 22. Where the desired carbon (D) is 760ppm. In case of unscheduled,

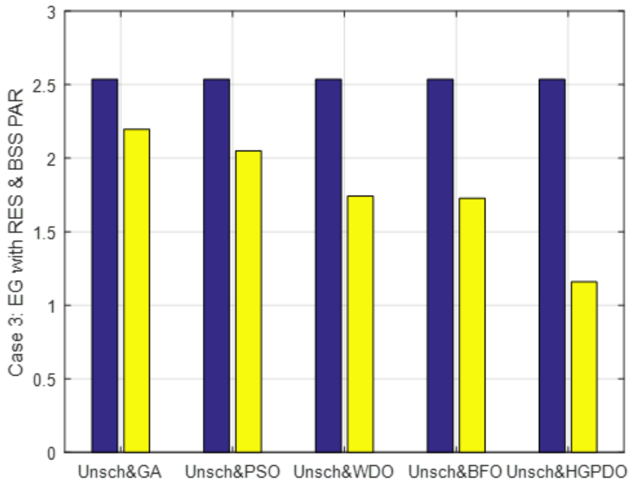

FIGURE 21. Case 3 PAR.

it is 968.3 ppm, which shows carbon emission is far from the desired range. While in GA, BPSO, WDO, BFO and HGPDO it is 671.6 ppm, 541.6 ppm, 374.8 ppm 567.5 ppm and 63.5 ppm, respectively. The reduction in carbon emission in this case for GA, BPSO, WDO, BFO and HGPDO is 11.63%, 28.73%, 50.68%, 25.39% and 91.64% respectively. In this case, WDO and HGPDO shows better results in terms of carbon emission reduction. Table 11 illustrates the comparison of desired, unscheduled carbon emission and emission by all scheduling algorithms.

TABLE 11. Case 3 carbon emission comparison.

Algorithm	Carbon emission (ppm)	Difference (ppm)	Reduction (%)
CO_2 concentration	760	- -	- -
Unscheduled	968.3	-208.30	-27.40% (increased)
GA	671.6	88.40	11.63%
BPSO	541.6	218.40	28.73%
WDO	374.8	385.20	50.68%
BFO	567.5	193.00	25.39%
HGPDO	63.5	696.5	91.64%

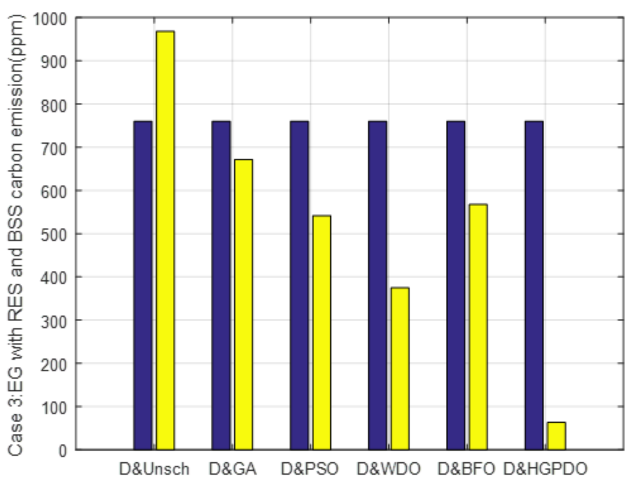

FIGURE 22. Case 3 carbon emission in (ppm).

TABLE 12. Delay comfort (minutes).

Appliances	GA	BPSO	WDO	BFO	HGPDO	Comfort(%) by HGPDO
Water heater (WH)	37	37	37	37	41	31.66%
Refrigerator	100	100	60	45	45	25.00%
HVAC	0	16	33	33	50	16.66%
Washing machine (WM)	04	12	12	12	32	46.66%
EV	100	70	100	62	31	48.33%
Lights	09	29	29	29	33	45.00%

D. USER COMFORT

1) DELAY AND COST COMFORT

UC is related to both EBC and scheduling wait time. Comfort is considered using equation (38) in terms of scheduling wait time in this work. Scheduling wait time is that the consumer must wait to turn on their appliances. Consumer will control their home appliances agreeing to scheduling pattern provided by controller for reduction in EBC. A consumer who desires to reduce the cost, he will compromise on comfort level. Figure 23 shows the average scheduling wait time of all home appliances scheduled by GA, HGPDO, WDO, PSO and BFO algorithms respectively. GA has no wait time in serving HVAC load. Our proposed algorithm scheduling wait time of all appliances is less than one hour. Table 12 displays the scheduling time of the home appliances in minutes and respective improvement in case of HGPDO algorithm.

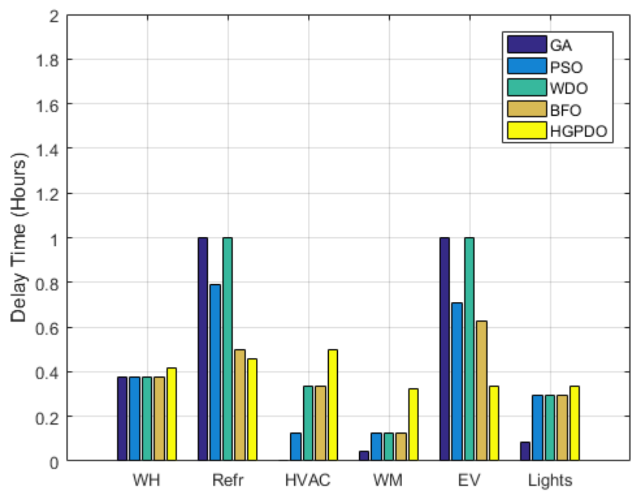

FIGURE 23. Waiting time of all appliances.

2) THERMAL COMFORT

Thermal comfort is calculated using equations (29) and (43) which is related to HVAC, cooling and heating (summer and winter season) and user given preference. Figure 24 shows the thermal comfort of our proposed HGPDO, GA, WDO, PSO and BFO algorithms. BPSO and WDO returns best values of TC. Also, it schedules the HVAC load on urgent basis with zero delay.

3) VISUAL COMFORT

Visual comfort is calculated using equations (39) and (41) which is related to number of lights, luminous intensity and user given preference. Figure 24 shows the visual comfort

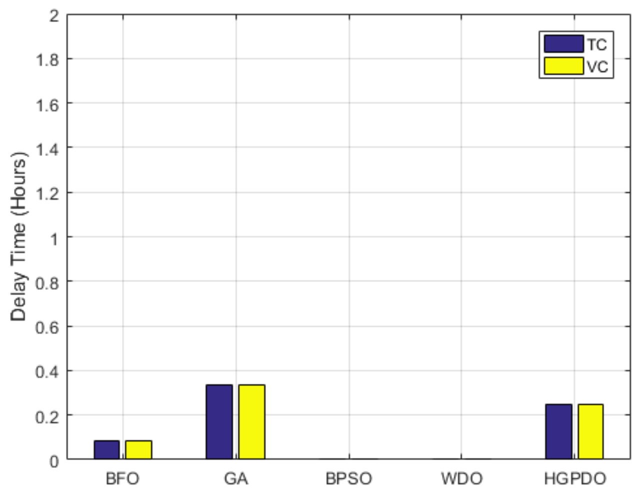

FIGURE 24. Thermal and visual comfort in minutes.

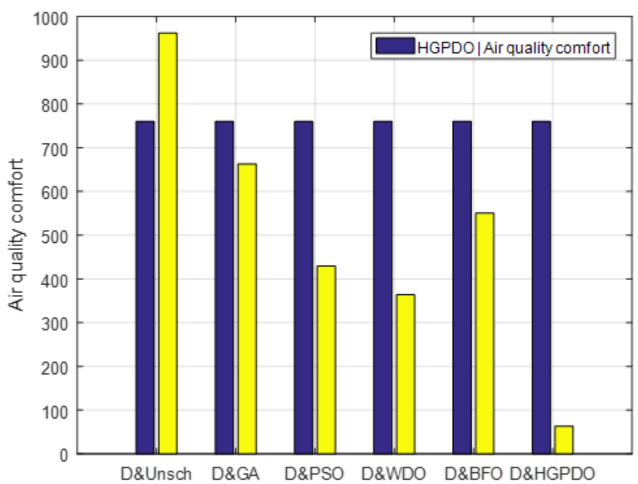

FIGURE 25. Air quality comfort in (ppm).

of our proposed HGPDO, GA, WDO, PSO and BFO. WDO returns the best values of VC because it schedules lights on urgent basis with zero delay.

4) AIR QUALITY COMFORT

Air quality comfort is calculated using equations (37) and (44). The AQC is related to carbon emission, electricity consumption and desired air freshness factor. Figure 25 shows the air quality comfort of our proposed HGPDO, GA, WDO, PSO and BFO. The proposed algorithm reduces the carbon emission, which results in less concentration of CO_2 in air, hence, the optimal AQC is achieved.

VI. CONCLUSION AND FUTURE WORK

The authors have proposed an efficient load scheduling and energy management controller for smart home building to reduce the electricity bill, PAR, carbon emission and improve UC in terms of visual, thermal, air quality and delay. This work considers a smart building utilizing power from EG, BSS and RES i.e., solar, thermal and wind power to shift load to peak hours and achieve the objectives. The huge HVAC load is scheduled with other different shiftable and smart appliances to reduce load. Each appliance in the smart home is scheduled using GA, BPSO, WDO, BFO and the proposed optimization technique, HGPDO. The proposed technique helps to find the most optimum schedule of each home appliance considering system constraints. The performance of the proposed scheme and heuristic algorithms are evaluated using real time pricing scheme via MATLAB simulations. Moreover, we compared the results of the proposed method with the GA, PSO, WDO and BFO to check its efficiency. Results demonstrate that the proposed algorithm and integration of RES and BSS reduces the electricity bill, PAR and CO_2 in Case 1, by 58.69%, 52.78% and 72.40%, in Case 2, by 47.55%, 45.02% and 92.90% and in Case 3, by 33.6%, 54.35% and 91.64%, respectively as compared with unscheduled. Moreover, the user comfort by our proposed HGPDO algorithm in terms of delay, thermal, air quality and visual improved by 35.55%, 16.66%, 91.64% and 45%, respectively.

This work is based on domestic smart home load in residential sector. It can be applied to a commercial and industrial sector, and can also be considered with a large number of appliances and onsite renewable energy generation.

In future, we will work on real time algorithms and will evaluate the performance of our proposed system for the same scenarios.

REFERENCES

[1] *International Energy Agency*. Accessed: Mar. 21, 2021. [Online]. Available:https://www.researchandmarkets.com/issues/electricity-demand
[2] *World Nuclear Association*. Accessed: Mar. 21, 2021. [Online]. Available:https://www.world-nuclear.org/nuclear-essentials/where-does-ourelectricity-come-from.aspx
[3] *International Energy Agency*. Accessed: Mar. 21, 2021. [Online]. Available:https://www.homeselfe.com/average-cost-electric-bills-rising-across-u-s/
[4] (Mar. 21, 2021). *Time and date forcaste, Hour-by-Hour Forecast for Islamabad, Pakistan*. [Online]. Available: https://www.timeanddate.com/weather/pakistan/islamabad/hourly
[5] A. Barragán-Escandón, J. M. O. Ruiz, J. D. C. Tigre, and E. F. Zalamea-León, "Assessment of power generation using biogas from landfills in an equatorial tropical context," *Sustainability*, vol. 12, no. 7, p. 2669, Mar. 2020.
[6] K. Aurangzeb, S. Aslam, H. Herodotou, M. Alhussein, and S. I. Haider, "Towards electricity cost alleviation by integrating RERs in a smart community: A case study," in *Proc. 23rd Int. Conf. Electron.*, Jun. 2019, pp. 1–6.
[7] 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.
[8] M. A. Judge, A. Manzoor, C. Maple, J. J. P. C. Rodrigues, and S. U. Islam, "Price-based demand response for household load management with interval uncertainty," *Energy Rep.*, Mar. 2021, doi: 10.1016/j.egyr.2021.02.064.
[9] K. Ullah, S. Ali, T. A. Khan, I. Khan, S. Jan, I. A. Shah, and G. Hafeez, "An optimal energy optimization strategy for smart grid integrated with renewable energy sources and demand response programs," *Energies*, vol. 13, no. 21, p. 5718, Nov. 2020.
[10] T. Li and M. Dong, "Real-time residential-side joint energy storage management and load scheduling with renewable integration," *IEEE Trans. Smart Grid*, vol. 9, no. 1, pp. 283–298, Jan. 2018.

[11] 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.

[12] A. Nawaz, G. Hafeez, I. Khan, K. U. Jan, H. Li, S. A. Khan, and Z. Wadud, "An intelligent integrated approach for efficient demand side management with forecaster and advanced metering infrastructure frameworks in smart grid," *IEEE Access*, vol. 8, pp. 132551–132581, 2020.

[13] A. Ahmad and J. Y. Khan, "Real-time load scheduling and storage management for solar powered network connected EVs," *IEEE Trans. Sustain. Energy*, vol. 11, no. 3, pp. 1220–1235, Jul. 2020.

[14] A. Ahmad and J. Y. Khan, "Real-time load scheduling, energy storage control and comfort management for grid-connected solar integrated smart buildings," *Appl. Energy*, vol. 259, Feb. 2020, Art. no. 114208.

[15] A. Ahmad and J. Y. Khan, "Roof-top stand-alone PV micro-grid: A joint real-time BES management, load scheduling and energy procurement from a peaker generator," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 3895–3909, Jul. 2019.

[16] G. Hafeez, Z. Wadud, I. U. Khan, I. Khan, Z. Shafiq, M. Usman, and M. U. A. Khan, "Efficient energy management of IoT-enabled smart homes under price-based demand response program in smart grid," *Sensors*, vol. 20, no. 11, p. 3155, Jun. 2020.

[17] 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.

[18] S. Umetani, Y. Fukushima, and H. Morita, "A linear programming based heuristic algorithm for charge and discharge scheduling of electric vehicles in a building energy management system," *Omega*, vol. 67, pp. 115–122, Mar. 2017.

[19] A. R. Kalair, N. Abas, Q. U. Hasan, M. Seyedmahmoudian, and N. Khan, "Demand side management in hybrid rooftop photovoltaic integrated smart nano grid," *J. Cleaner Prod.*, vol. 258, Jun. 2020, Art. no. 120747.

[20] K. Aurangzeb, M. Alhussein, K. Javaid, and S. I. Haider, "A pyramid-CNN based deep learning model for power load forecasting of similar-profile energy customers based on clustering," *IEEE Access*, vol. 9, pp. 14992–15003, 2021.

[21] K. G. D. Santo, S. G. D. Santo, R. M. Monaro, and M. A. Saidel, "Active demand side management for households in smart grids using optimization and artificial intelligence," *Measurement*, vol. 115, pp. 152–161, Feb. 2018.

[22] B. Celik, R. Roche, S. Suryanarayanan, D. Bouquain, and A. Miraoui, "Electric energy management in residential areas through coordination of multiple smart homes," *Renew. Sustain. Energy Rev.*, vol. 80, pp. 260–275, Dec. 2017.

[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] L. Yu, T. Jiang, and Y. Zou, "Distributed real-time energy management in data center microgrids," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 3748–3762, Jul. 2018.

[25] L. Yu, T. Jiang, and Y. Zou, "Online energy management for a sustainable smart home with an HVAC load and random occupancy," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 1646–1659, Mar. 2019.

[26] M. A. Hannan, M. G. M. Abdolrasol, M. Faisal, P. J. Ker, R. A. Begum, and A. Hussain, "Binary particle swarm optimization for scheduling MG integrated virtual power plant toward energy saving," *IEEE Access*, vol. 7, pp. 107937–107951, 2019.

[27] S. Williams and M. Short, "Electricity demand forecasting for decentralised energy management," *Energy Built Environ.*, vol. 1, no. 2, pp. 178–186, Apr. 2020.

[28] K. Aurangzeb, S. Aslam, S. I. Haider, S. M. Mohsin, S. U. Islam, H. A. Khattak, and S. Shah, "Energy forecasting using multiheaded convolutional neural networks in efficient renewable energy resources equipped with energy storage system," *Trans. Emerg. Telecommun. Technol.*, Dec. 2019, Art. no. e3837.

[29] A. Khalid, N. Javaid, M. Guizani, M. Alhussein, K. Aurangzeb, and M. Ilahi, "Towards dynamic coordination among home appliances using multi-objective energy optimization for demand side management in smart buildings," *IEEE Access*, vol. 6, pp. 19509–19529, 2018.

[30] A. Ghassemi, P. Goudarzi, M. R. Mirsarraf, and T. A. Gulliver, "A stochastic approach to energy cost minimization in smart-grid-enabled data center network," *J. Comput. Netw. Commun.*, vol. 2019, pp. 1–11, Mar. 2019.

[31] A. Imran, G. Hafeez, I. Khan, M. Usman, Z. Shafiq, A. B. Qazi, A. Khalid, and K.-D. Thoben, "Heuristic-based programable controller for efficient energy management under renewable energy sources and energy storage system in smart grid," *IEEE Access*, vol. 8, pp. 139587–139608, 2020.

[32] C. Wenge, R. Pietracho, S. Balischewski, B. Arendarski, P. Lombardi, P. Komarnicki, and L. Kasprzyk, "Multi usage applications of Li-ion battery storage in a large photovoltaic plant: A practical experience," *Energies*, vol. 13, no. 18, p. 4590, Sep. 2020.

[33] S. Ali, I. Khan, S. Jan, and G. Hafeez, "An optimization based power usage scheduling strategy using photovoltaic-battery system for demand-side management in smart grid," *Energies*, vol. 14, no. 8, p. 2201, 2021.

[34] G. Hafeez, N. Islam, A. Ali, S. Ahmad, and M. U. A. K. S. Alimgeer, "A modular framework for optimal load scheduling under price-based demand response scheme in smart grid," *Processes*, vol. 7, no. 8, p. 499, Aug. 2019.

[35] C. Bharathi, D. Rekha, and V. Vijayakumar, "Genetic algorithm based demand side management for smart grid," *Wireless Pers. Commun.*, vol. 93, no. 2, pp. 481–502, Mar. 2017.

ATEEQ UR REHMAN is currently pursuing the M.Sc. degree in computer system engineering with the University of Engineering and Technology, Peshawar, Pakistan. He has authored or coauthored over in peer-reviewed research articles in reputed international journals and papers in conferences. His research interests include optimization, planning, energy management, and machine learning applications in smart grids/microgrids.

ZAHID WADUD received the B.Sc. and master's degrees in electrical engineering from the University of Engineering and Technology, Peshawar, Pakistan, in 1999 and 2003, respectively, and the Ph.D. degree from the Capital University of Science and Technology, Islamabad Pakistan, with the thesis entitled Energy balancing with sink mobility in the design of underwater routing protocols. He is currently working as an Assistant Professor with the Department of Computer Systems Engineering, University of Engineering and Technology. He has published over dozen state-of-the-art publications in the renowned international journals. His research interests include wireless sensor networks, energy efficient networks and subsystems, mathematical modeling of wireless channels, embedded systems, and sensors interface.

RAJVIKRAM MADURAI ELAVARASAN received the B.E. degree in electrical and electronics engineering from Anna University, Chennai, India, and the M.E. degree in power system engineering from the Thiagarajar College of Engineering, Madurai, India. He worked as an Associate Technical Operators with the IBM Global Technology Services Division. He worked as an Assistant Professor with the Department of Electrical and Electronics Engineering, Sri Venkateswara College of Engineering, Chennai. He currently works as a Design Engineer with the Electrical and Automotive Parts Manufacturing Unit, AA Industries, Chennai. He also works as a Visiting Scholar with the Clean and Resilient Energy Systems (CARES) Laboratory, Texas A&M University, Galveston, TX, USA. He has published articles in international journals, and papers in international and national conferences. His research interests include solar PV cooling techniques, renewable energy and smart grids, wind energy research, power system operation and control, artificial intelligence, control techniques, and demand-side management. He received the Gold Medal for his master's degree. He is a recognized Reviewer in reputed journals, namely the IEEE Systems, IEEE Access, *IEEE Communications Magazine*, *International Transactions on Electrical Energy Systems* (Wiley), *Energy Sources, Part A: Recovery, Utilization and Environmental Effects* (Taylor and Francis), *Scientific Reports* (Springer Nature), *Chemical Engineering Journal* (Elsevier), and *CFD Letters and Biotech* (Springer).

GHULAM HAFEEZ received the B.Sc. degree in electrical engineering from the University of Engineering and Technology, Peshawar, Pakistan, and the M.S. and Ph.D. degrees in electrical engineering from COMSATS University Islamabad, Islamabad, Pakistan. He is a lifetime Charted Engineer from Pakistan Engineering Council. He is currently working as a Manager with the University-Industry Linkages/Research Operations Development in the Directorate of ORIC, University of Engineering and Technology, Mardan, Pakistan. Prior to this, he was a Lecturer with the Department of Electrical Engineering, University of Engineering and Technology. He also worked as a Lecturer with the University of Wah, Wah, Pakistan. He has also worked as a Research Associate with COMSATS University Islamabad, where his research focus was computational intelligence, forecast process, energy management, operation of electricity market, and electric vehicles in smart power grids. His industrial experience includes working as an Optimization Engineer for Alcatel-Lucent and PTCL, Islamabad. He has authored or coauthored in peer-reviewed research articles in reputed international journals and papers in conferences. His research interests include sustainable and smart energy, cities and societies, smart grids; applications of deep learning and blockchain in smart power grids; and stochastic techniques for power usage optimization in smart power 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, in 2010. He is currently working as a Professor with the Department of Electrical Engineering, University of Engineering Technology, Mardan, Pakistan. 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.

ZEESHAN SHAFIQ received the bachelor's, master's, and Ph.D. degrees in electrical engineering from the University of Engineering and Technology, Peshawar, Pakistan, in 2009, 2012, and 2018, respectively. His research interests include vehicular ad hoc networks, intelligent transportation systems, and unmanned aerial vehicles. 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 unmanned aerial vehicles with the Centre of Excellence in Telecommunications. He has also reviewed many research articles for well-reputed journals, including IEEE ACCESS and IEEE Technical Review Journals.

HASSAN HAES ALHELOU (Senior Member, IEEE) is currently with the School of Electrical and Electronic Engineering, University College Dublin, Dublin, Ireland. He is also a Faculty Member of Tishreen University, Lattakia, Syria. He has published more than 130 research articles in the high quality peer-reviewed journals and more than 30 research articles in the high quality international conferences. He has participated in more than 15 industrial projects. His major research interests include power systems, power system dynamics, power system operation and control, dynamic state estimation, frequency control, smart grids, micro-grids, demand response, load shedding, and power system protection. He has also performed reviews for high prestigious journals, including IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, *Energy Conversion and Management*, *Applied Energy*, and the *International Journal of Electrical Power and Energy Systems*. He was a recipient of the Best Young Researcher in the Arab Student Forum Creative, among 61 researchers from 16 countries at Alexandria University, Egypt, in 2011 and the Outstanding Reviewer Award from many journals, such as *Energy Conversion and Management (ECM)* in 2016, *ISA Transactions* in 2018, *Applied Energy* in 2019, and many other awards. He is included in the 2018 and 2019 Publons list of the top 1% Best Reviewer and researchers in the field of engineering.