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Intelligent Optimization Framework for Efficient Demand-Side Management in Renewable Energy Integrated Smart Grid

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ABSTRACT The implementation of real-time price-based demand response program and integration of renewable energy resources (RESs) improves efficiency and ensure stability of electric grid. This paper proposes a novel intelligent optimization based demand-side management (DSM) framework for smart grid integrated with RESs. In the intelligent DSM framework the artificial neural network (ANN) forecasts energy usage behavior of consumers and real-time price-based demand response program (RTPDRP) of electric utility company (EUC). The smart energy management controller of the proposed intelligent DSM framework adapts forecasted energy usage behavior of consumers using forecasted RTPDRP to create operation schedule. The consumers implement the created schedule to minimize energy cost, peak load, carbon emission subjected to improving user comfort and avoiding rebound peaks. Simulations are conducted using our proposed hybrid genetic ant colony (HGAC) optimization algorithm to create schedule for three cases: EUC without RESs, EUC with RESs, and EUC with both RESs and storage technologies. To endorse the applicability and productivity of the proposed DSM framework based on HGAC optimization algorithm with five existing algorithms based frameworks. Simulation results show that the proposed DSM framework is superior compared with the existing frameworks in terms of energy cost minimization, peak load mitigation, carbon emission alleviation, and user discomfort minimization. The proposed HGAC optimization algorithm reduced electricity cost, carbon emission, and peak load by 12.16%, 4.00%, and 19.44% in case I; by 26.8%, 20.71%, and 33.3% in case II; and by 24.4%, 16.44%, and 37.08% in case III, respectively, compared to without scheduling.

INDEX TERMS Demand-side management, battery energy storage systems, photovoltaic, demand response, scheduling, smart grid.

NOMENCLATURE

ANN	Artificial neural network.
AMI	Advanced metering infrastructure.
ACO	Ant colony optimization.
BFO	Bacterial foraging optimization.
BPSO	Binary PSO.
BILP	Binary integer linear programming.
CP	Convex programming.
DGs	Distributed generations.
DSM	Demand-side management.
DP	Dynamic programming.
DR	Demand response.
EDE	Enhanced differential evolution.

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ESS	Energy storage system.
ECC	Energy consumption controller.
EUC	Electric utility company.
EMC	Energy management controller.
EVs	Electric vehicles.
GA	Genetic algorithm.
HGAC	Hybrid genetic ant colony.
H2V	Home to vehicle.
IBR	Inclining block rate.
MOWDO	Multi-objective WDO.
MOGA	Multi-objective GA.
MPC	Model predictive control.
MILP	Mixed integer linear programming.
PV	Photovoltaic.
PAR	Peak to average ratio.
PSO	Particle swarm optimization.
PEVs	Plugin electric vehicles.
RES	Renewable energy resources.
RTPDRP	Real-time price-based demand response program.
RTP	Real-time pricing.
RDSM	Robust DSM.
SGs	Smart grids.
SMs	Smart meters.
SPG	Smart power grid.
TLBO	Teaching learning based optimization.
TLGO	Teaching learning genetic optimization.
V2G	Vehicle to grid.
WDO	Wind driven optimization.
A_k	Actual value.
A^{pv}	Area of solar panel.
$\theta(t)$	Carbon emission.
$ES_{ch}(t)$	Charging state.
$ES_{dis}(t)$	Discharging state.
η^{ESS}	Efficiency of the batteries.
Γ_{ω}^{t}	Energy consumption of rechargeable appliances.
Γ_{F}^{t}	Energy consumption of fixed appliances.
Γ_{s}^{t}	Energy consumption of non-interruptible appliances.
Γ_{ν}^{t}	Energy consumption of fixed appliances.
Γ_{ϕ}^{t}	Energy consumption of elastic appliances.
η^{pv}	Efficiency of solar panel.
F_k	Forecast value.
b_i	Hidden layer.
$\phi(t)$	Imported electricity.
z_j	Input elements.
y_i	Input to the hidden nodes.
β_j	Linear weight between input and output nodes.
LOT	Length of operation time.
N	Number of training samples.
A	Number of all appliances.
$F(t)$	Output vector.
$x_{q_c}(t)$	ON/OFF status of appliances.
α	Operation start time.
β	Operation end time.
$Temp$	Outside environment temperature.
ρ_{q_c}	Power rating of appliances.
$\delta(T)$	Peak to average ratio.
P^{pv}	Power generated by solar panel.
$EP(t)$	Real time electricity price.
Q	Set of fixed appliances.
S_r	Set of non-interruptible appliances.
W	Set of rechargeable appliances.
I_{rr}	Solar irradiance.
$\psi 1, \psi 2$	Shape factors.
$\lambda 1, \lambda 2$	Scale factors.
$Schd(t)$	Scheduled load.
$SE(t)$	Stored energy in ESS.
E_{ϕ}	Total energy consumption.
$E_{total}(t)$	Total energy consumption.
$Unschd(t)$	Unscheduled load.
W_i	Weight factor.
w_{ij}	Weight between the neurons of input layer and hidden layer.

I. INTRODUCTION

Throughout, the world energy demand is rapidly increasing with the drastic increase in population and modern technology. Today, fossil fuels have a major contribution to electricity production. In the US, electricity production causes 26.9% carbon emission after transportation [1]. To reduce the emission of gases that cause global warming, researchers are working to replace the existing power plants that mostly run on fossil fuels with renewable energy sources (RES). However, the installation of large numbers of RES will create instability in the power system or the waste of excess amount of energy. To reduce the use of fossil fuels and govern RES efficiently, renovation of traditional grids with smart grids (SGs) is needed.

A smart grid is a smart electricity network that intelligently accommodate consumers and electric EUCs companies (EUCs) that actively participate in electricity market. The purpose is to ensure sustainable, cheaper, and secure electricity supply to consumers subjected to power system stability. The SG works alongside integrate many types of equipment like smart home appliances, smart meters (SM), energy storage systems (ESS), and RES. The SG uses modern techniques to govern power generation plants, transmission and distribution network. The SG have advanced monitoring infrastructure (AMI) to collect and distribute data of energy demand, supply, and price between consumers and EUCs. It builds two-way communication of providing information, such that consumers can reduce electricity bills by using the minimum amount of energy according to price information provided by AMI. In contrast, the EUCs can achieve the best demand-side management (DSM) and minimum generation cost by adjusting power generation timing.

Recently in literature, scientists introduced various DSM strategies that help the consumer to consume minimum energy either by integrating RES or operating their loads during off-peak hours. In [2], authors considered the thermal storage capacity of thermostatic devices and ESS integrated photovoltaic (PV) panels. The authors proposed a heuristic forward-backward algorithm to reduce the cost of the thermal appliances and also suggested peak flattening scheme to prevent the peak occurrence in the power system. In [3], authors discussed the critical role of optimal energy algorithm in order to enhance the performance of EUCs, energy saving at consumer end and environmental benefits. Authors studied electricity cost and user discomfort minimization by proposing the genetic algorithm (GA) and solved these problems in two stages i.e., the first stage optimization involves the electricity cost reduction, while second stage optimization is based on the first stage optimization, with no increase in the cost of purchased electricity in [4].

Authors considered a case of residential consumers with integrated ESS and PV to solve energy management problem in [5]. Their proposed algorithm minimized electricity cost and PAR by scheduling the operation time of different appliances. In [6], authors engaged consumers of both residential and commercial areas for solving power usage scheduling problem. They proposed the particle swarm optimization (PSO) algorithm to reduce peak to average ratio (PAR) and electricity cost by integrating RES, and electric vehicles (EVs). The authors studied PAR, electricity cost minimization, and also considered user comfort maximization while solving power usage scheduling in [7]. They combined real-time pricing (RTP) with inclining block rate (IBR) tariff to limit high power consumption at times of low costs, and also to improve PAR. Similarly, authors introduced artificial intelligence to the system design, which provides various solution for energy consumption based on past experience in [8]. For consumer suggestion, the user feedback link is also added in this system. Thus providing personalized services in energy saving. Likewise in [9], authors proposed about improved version of automation system for building in order to improve efficiency in commercial apartments. This system will allow the consumer to monitor and control their energy consumption and also to notice their energy saving potentials.

Though, literature discussed provides a good start for understanding DSM in SG. However, the DSM problem is a challenging problem due to the nonlinear behavior of consumers, more volatile and intermittent RES, limited fossil-fuel sources. Moreover, the focus of the existing literature is on electricity cost minimization, PAR alleviation, and devices delay reduction. Also, the use of intrinsic models is not adequate for solving DSM problem to achieve objectives like electricity cost, peak energy consumption, PAR, user discomfort, and carbon foot print minimization simultaneously. Because the intrinsic models' performance is compromised due to inherit limitation and incompetence to handle conflicting parameters. Thus, to cater this dilemma hybrid and integrated models are the need of the day. In this regard, a novel integrated DSM framework based on ANN and our proposed hybrid genetic ant colony optimization (HGAC) optimization algorithm is introduced for solving problems accompanied with intrinsic models while catering DSM problem. The novelty and main contributions of this work are demonstrated as follows.

- The ANN forecaster is integrated with smart energy management controller based HGAC optimization algorithm in DSM framework to forecast exogenous signals like load, temperature, solar irradiance, and RTPDRP. The purpose is to perform efficient DSM via scheduling energy usage profile of residential buildings under the forecasted RTPDRP.
- An integrated distributed generations (DGs) system of solar energy system, EVs, battery storage system, and EUCs is developed to solve DSM problem using RTPDRP.
- Consumers load and DGs like solar energy system, EVs, battery storage system are made smart and controlable to actively participate in DSM to minimize electricity costs, PAR, carbon emission, and consumer discomfort, simultaneously.
- A RTPDRP is introduced that broadcasts pricing signal to the consumers to take part in load shifting, valley filling, peak clipping, and load demand curve smoothing to solve DSM problem.
- Consumers load is classified into shiftable appliances, elastic appliances, uninterruptible appliances, and rechargeable appliances, to show more flexibility and actively participation in RTDRP to solve DSM problem.
- The DSM problem is mathematically formulated as minimization problem subject to practical power usage, DGs, EUCs, and RTPDRP constraints for the purpose to ensure energy cost savings, minimize carbon emissions, alleviate PAR, and improve user comfort.
- A hybrid optimization HGAC algorithm is introduced to solve the formulated DSM problem.
- Performance of the proposed optimization algorithm is endorsed by comparing it to intrinsic optimization algorithms like PSO [10], GA [11], wind driven optimization (WDO) [12], and ant colony optimization (ACO) [13] in terms of electricity cost, energy consumption, PAR, waiting time, and carbon footprint.
- The simulation process is divided in three cases. First case is conducted without the integration of RES and ESS, second case the consumer is considered with integrated RES which shows the importance of RES in power system, third case, the consumer is considered with integrated RES and ESS.
- Simulation results illustrates that proposed HGAC optimization algorithm outperforms the intrinsic algorithms.

The remaining sections of this work are arranged as follows. The sections II discuss the related work. The proposed system model is designed and briefly explained in section III, section IV presents proposed algorithm, section V presents the simulation and results, and finally the paper is concluded in section VI.

II. RELEVANT LITERATURE SURVEY

Recently, in literature various authors work on solving DSM in SG. In this context, some recent related work to the theme is discussed as follows.

In [14], the authors proposed a MILP based scheme that reduced PAR by 48% with microgrid, and similarly, electricity costs decreased by 45% without and 80% with microgrid integration. The authors also developed a forecasting system (EDE-ANN), that helps a user to communicate with the microgrid and power grid in purchasing electricity required by the consumer. But on the contrast, the authors did not consider carbon emission from energy consumption. Authors introduced DSM system, which curtail the electricity expense via scheduling smart appliances in home [15]. The authors used knapsack problems to formulate the constrained optimization problem, and then solved by GA, binary PSO (BPSO), WDO, bacterial foraging optimization (BFO), and hybrid of GA-PSO (HGPO). The authors integrated RES and ESS that reduced PAR and electricity bills by 21.55% and 19.94% respectively. In [16], the authors proposed PSO to solve PSP for scheduling smart home appliances which in turn reduced electricity bills and PAR. They also compared PSO with GA and PSO has optimum results than GA in terms of electricity bills, PAR, and maximum user comfort but they ignored carbon emission. In [17], the authors proposed a generic architecture for DSM and a combination of time of use (ToU) tariff and use full form on first instance IBR. They introduced ACO for scheduling home appliances that reduced PAR and electricity bills efficiently. They also minimized user discomfort but ignored carbon emission. The authors introduced DSM framework to benefit the consumer by searching out for a sufficient amount of solar energy [18]. They also developed two loops systems, one is model predictive control (MPC) to control power flow if any uncertain disturbance occurs while second is the optimal control method that will schedule the power flow of the overall system over the scheduling horizon.

In [19], the authors introduced the multi-objective WDO (MOWDO) and multi-objective GA (MOGA) for energy optimization in SG considering demand response (DR) program and high penetration of RES. Their objectives were operation cost, pollution emission, and availability optimization. The authors in [20], assumed that consumer is provided with a smart meter which has an energy consumption controller (ECC) unit. This ECC units are via LAN connected with neighbors for sharing power utilizing information. Their objectives were reduction in PAR and electricity bills. They used ECC units to transfer the maximum of the peak load to off-peak hours and this minimizes the consumption cost by 21% and PAR by 24%. In [21], the authors represented a behavior-driven price-based MPC model which control different home appliances, and nodal pricing method for controlling different costs. They tested these two methods on 15,000 buildings and reduced generation costs by 21% and PAR by 17%. However, they ignored carbon emission and user discomfort.

In [22], the authors developed a Nash-game-theory-based optimization model to minimize cost, PAR, and user discomfort. This optimization model reduced the cost in the summer season by 9.17% and in the winter season by 9.68%. Similarly, PAR is minimized in the summer season by 1.76, and in the winter season reduced by 1.81. However, the authors ignored carbon emission.The authors in [23] modeled a HEM controller based on BFOA, WDO, GA, BPSO, and GA + BPSO (GBPSO) for minimizing electricity consumption and PAR. The GBPSO is the hybrid of GA and BPSO and has better results for both cost and PAR, while GA reduced PAR by 34% and BPSO reduced cost by 36%. Despite these objectives, they did not consider carbon emission and user comfort. The authors in [24], introduced the binary integer linear programming (BILP) algorithm and compared their results with the mixed integer linear programming (MILP) technique. Their objective was to reduce cost, and reduced it by 35%. However, they did not use any RES. In [25], the authors formulated the BILP technique for scheduling smart home appliances to minimize electricity consumption cost and linearize the load profile curve. They used plugin electric vehicles (PEVs), ESS, and RES for putting less load on the grid. However, they did not consider consumer satisfaction. In [26], the authors considered a smart home with PV, ESS, and PEV to minimize the home economy. They introduced convex programming (CP) for controlling the essential parameters of ESS, so that the consumer does not depend on EUCs during the on-peak time slots. They considered bi-directional power flow modes like home to vehicle (H2V) and vehicle to grid (V2H) that participate in DSM. The V2H mode has a 2.6% lower electric cost than unidirectional power flow mode H2V. In [27], the authors presented a bi-level optimization method including upper capacity and lower operation optimizations. They compared their results with the system having no storage system. Their proposed technique significantly reduced the overall cost, and shifted most of the load to off-peak hours, and also increased the use of RES.

In [28], the authors proposed robust DSM (RDSM) framework, which has two parts. The first is load scheduling to minimize the cost, and the second part composed of dynamic programming (DP) for power management to enhance cost reduction using RES. They compared their results with column-and-constraint generation and RDSM has the best results for both cost and PAR. The authors in [29], [30], developed an energy management controller (EMC) for DSM. Energy consumption, cost, and PAR are reduced by using fuzzy logic and heuristic optimization techniques, which are BAT, FP, and HFBA algorithms. In the results, BAT has reduced cost by 9.0877% while the FP and HFBA by 9.0459% and 8.6154%, respectively. Similarly, HFBA has reduced PAR by 25.45%, while the FP and BAT by 9.4907% and 23.91%, respectively. However, they did not consider carbon emission in their system. The authors in [31] introduced DSM and GA-DSM and compared their results. GA-DSM has a more reliable result of reducing the overall load than DSM by reducing 21.91%. However, the authors ignored electricity cost, carbon emission, and user comfort. In [32], the authors introduced a hybrid teaching learning genetic optimization (TLGO) by combining GA and teaching learning based optimization (TLBO) to schedule the residential loads. They focused on user discomfort and electricity cost. According to TLGO, GA, and TLBO electricity cost was reduced by 33%, 31%, and 31.5%, respectively. Similarly, GA, TLBO, and TLGO minimized the user discomfort by 2.37, 2.14, and 1.83, respectively. However, they did not consider PAR and carbon emission. The authors in [33], reduced the pressure on EUCs and users by using DSM. They also used SBA and BFO to facilitate the HEMS in scheduling home appliances. ToU is introduced to find out the cost in efficient way. Their results show that cost and PAR are efficiently reduced. In [34], the authors introduced HEMS with a scheduler to schedule the home appliances. They aimed to reduce the electricity cost and maximize user comfort. The HEMS helped by combining GA with RTP and IBR to regulate the instability of the system. The simulation results show that this scheme has better results for both consumers and suppliers. In [35], the authors modeled DSM as a multi-objective optimization problem to reduce PAR and increase consumer satisfaction. They proposed a distributed energy scheduling algorithm to achieve the desired objective. A multiobjective immune algorithm is adopted for Pareto optimal solution of multimicrogrid design [36]. The objectives of this work are utility maximization for the microgrids, utility maximization for the power grid, and maximize a sum of the stored energy levels within the multimicrogrid network. Similarly, a multi-objective cooperative approach for the energy management of multimicrogrid is developed in [37]. Results show that the developed model is effective in terms greenhouse gas emission, voltage drop, and losses as compared to benchmark schemes. A collaborative framework is developed for solving energy dispatch problem of multi-stakeholder multiple microgrids [38].

The above models discussed are valuable asset of stat-of-the-art works and capable to solve DSM problem in SG. However, every model has their inherit limitation and suitable for the specified constraints, objectives, and assumptions. Thus, state-of-the-art work is concluded with following findings: (i) there is no model exist which is perfect in all aspects, (ii) there are some parameters, which are conflicting in nature due which tradeoff exist, increasing one will results a decrease in the other and vice versa. In this context, a system model is proposed based on ANN and novel algorithm namely hybrid genetic ant colony (HGAC) optimization algorithm for solving problems accompanied with intrinsic models while catering DSM problem.

III. PROPOSED ARCHITECTURE OF DEMAND SIDE MANAGEMENT SYSTEM

In this section, the proposed system model of smart power grid (SPG) comprises ANN based forecaster, different types of loads in smart home, DGs, EMC for controlling and monitoring all the activities as shown in Figure 1. To get a secured management or delivery of energy, it is important that all the communication messages to be delivered in a secure manner via wireless communication infrastructure between smart appliances and EMC as shown in Figure 2.

The proposed system model is an integrated model of household energy demand model, energy supply model consisting of RES and power grid, and load scheduling model to meet the energy requirements of the consumers. First, ANN forecaster is trained using historical load and DR data to forecast RTPDRP and power usage pattern of consumers. The ANN in this work is adopted due to its capability to handle nonlinear behavior of consumers. The ANN forecaster is data driven. The dataset used in this work is taken from midwest independent system operator federal energy regulatory commission [39]. The dataset have hourly load and price data having key features like temperature, dew point, and humidity. The dataset is for a period of one year from September 2008 to September 2009. The dataset is divided into training set (80%) and testing set (20%). The ANN three layer structure is defined in this work: input layer, hidden layer, and output layer. The ANN is feed-forward network where neurons of each layer are connected to the neurons of succeeding layer via synaptic weights, as shown in Figure 3. The historical dataset is given as input to ANN to create mapping of input and output vector, which is mathematically modeled as:

$$F = \sum_{i=1}^{n} W_i f(y_i) + \sum_{j=1}^{m} \beta_j z_j, \tag{1}$$

where

$$f(y_i) = \frac{1}{1 + \exp(-y_i)}$$

$F(t)$ is output vector shows forecast results, W_i is weight factor between input and output nodes, β_j is the linear weight between input and output nodes, z_j represents input elements, and y_i is the input to the hidden nodes. The Levenberg–Marquardt optimization algorithm and sigmoidal transfer function are used for training of the ANN. The y_i is computed as follows:

$$y_i = \sum_{j=1}^{3} w_{ij} z_j + b_i, \tag{2}$$

where w_{ij} is the weight between the neurons of input layer and hidden layer, and b_i is the bias added at the hidden layer. The learning process will be stopped when the maximum number of epochs are reached or error function is minimized to the predefined tolerance. The error function is

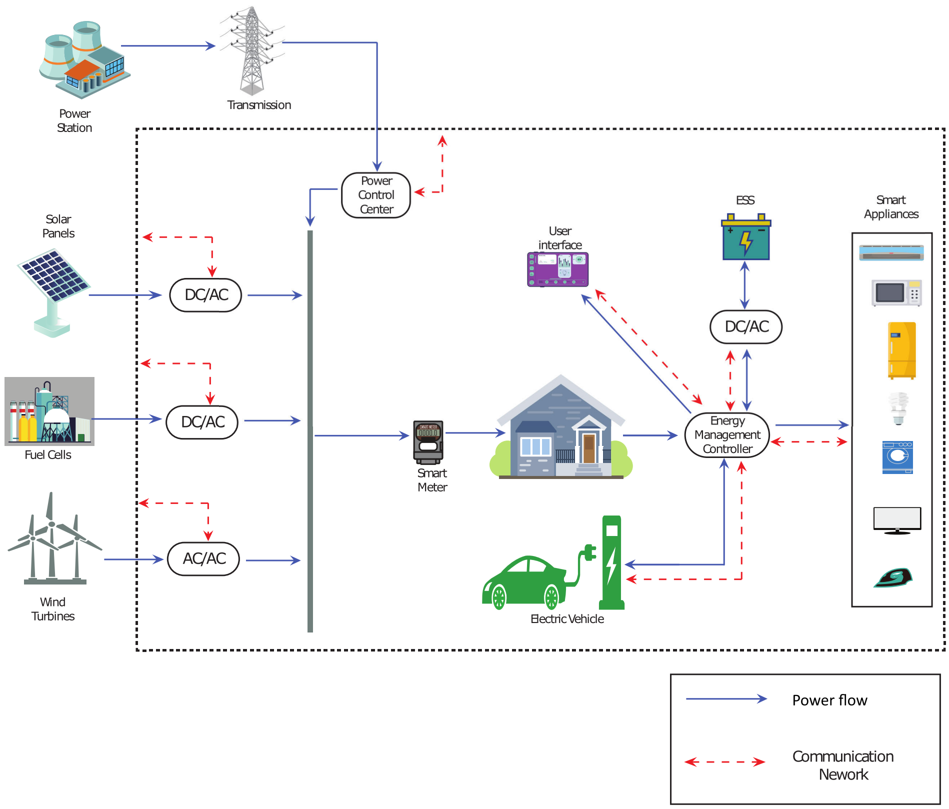

FIGURE 1. **Proposed system model for demand side management.**

defined as follows:

$$E = \frac{1}{N}\sum_{k=1}^{N}(A_k - F_k)^2, \tag{3}$$

where A_k and F_k are the actual and forecasted outputs of the network at kth pattern, respectively, and N is the number of training samples employed. The forecasted values based on ANN closely follow the target values, which indicates that error is low and the results obtained are accurate. For more explanation regarding ANN forecast engine design interested readers are referred to [40].

We have divided a day in equal and constant duration of time by using quasi static model. Let us consider that each time slot t is subset of T the observed time $T = \{t \in T \mid t_1, t_2, t_3\}$. Each time slot t is equal to 1 hour so that each appliance has enough time to operate and finish the running activity. It is further considered that A is the number of all appliances enclosed in set S, and all the appliances of a consumer are represented as $S = \{s \in S \mid s_1, s_2, s_3, \ldots, s_A\}$. Therefore, the energy consumption by an appliance in 24 hours is given as:

$$E_{s_1} = E_{1,s_1} + E_{2,s_1} + E_{3,s_1} + \ldots + E_{\tilde{T},s_1}. \tag{4}$$

To calculate consumers energy consumption of appliances E_ϕ is given as:

$$E_\phi = \sum_{t=1}^{\dot{T}} \tilde{T} \sum_{a=1}^{A}(E(t, a_a)). \tag{5}$$

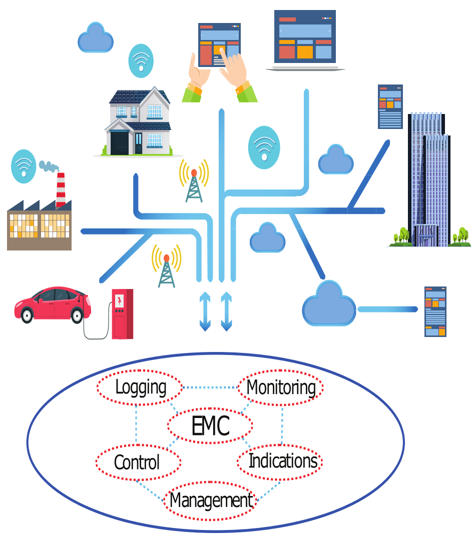

FIGURE 2. **The interaction of EMC to smart appliance for demand side management.**

In the following section, we placed all the consumer appliances in different categories on the basis of their characteristics, i.e., power rating, weather conditions and consumer's preferences.

A. FIXED APPLIANCES

These appliances cannot be managed and their demand can be satisfied on-demand independent of cost rising factor. For example lights, fans etc. Consider that C is the number

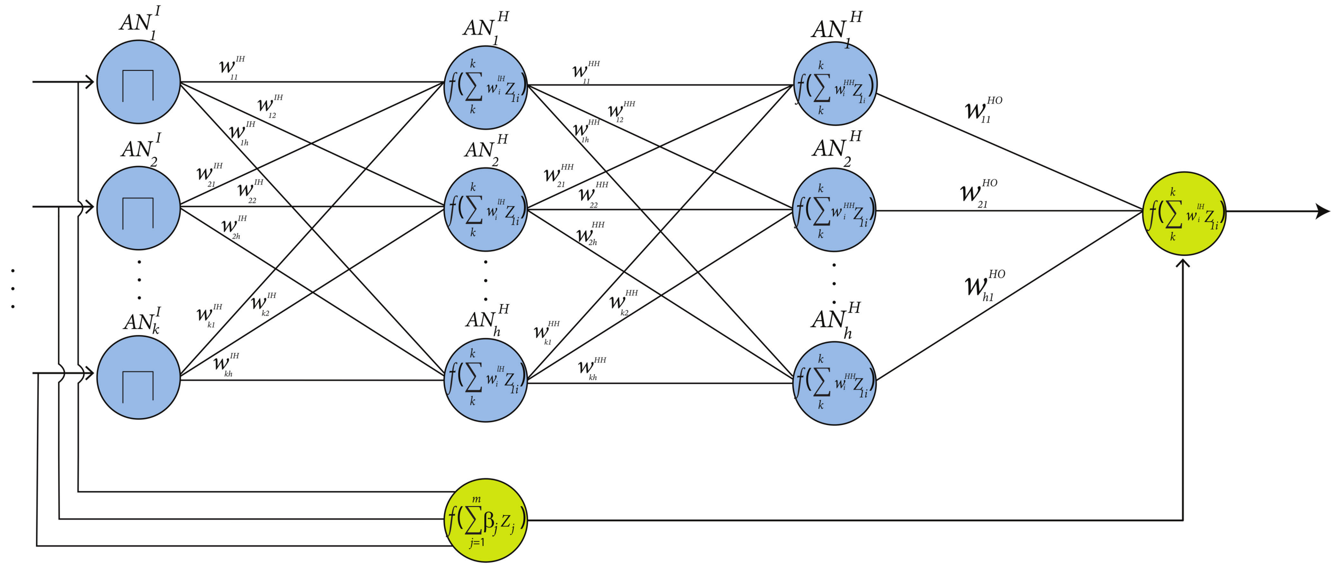

FIGURE 3. ANN feed-forward forecaster with single input layer, two hidden layers, and an output layer forecasting RTPDRP and power usage pattern.

of all fixed appliances placed in a set $Q = \{q \in Q \mid q_1, q_2, q_3, \ldots, q_C\}$. The power rating of each appliance in a given time slot is represented as ρ_{q_c}. The total power consumption by these appliances is given as:

$$\Gamma_{\nu}^{t} = \sum_{t=1}^{T} \sum_{q_c \in Q} (\rho_{q_c}(t) x_{q_c}(t)). \tag{6}$$

where $x_{q_c}(t)$ is the ON/OFF state of a fixed appliance and its value depends on the random probability. The power consumed by the fixed appliances must obey the following the constraint:

$$\Gamma_{\nu}^{min} \leq \Gamma_{\nu}^{t} \leq \Gamma_{\nu}^{max} \quad \forall t \in T. \tag{7}$$

Constraint (7) ensures that the energy consumption of fixed appliances must be within the lower Γ_{ν}^{min} and upper Γ_{ν}^{max} limit defined for energy consumption by the controller.

B. SHIFTABLE APPLIANCES

The shiftable appliances are alternatively named as schedulable appliances. The time of operation and power consumption of such type appliances can be managed to achieve minimum electricity cost and PAR. There are different types of schedulable appliances represented by set S. Based on their characteristics, we divided them into three categories that are discussed below.

1) ELASTIC APPLIANCES

The time of operation and power consumption pattern of these appliances can be managed by the consumer according to their comfort zone. These appliances are also known as thermodynamically controlled appliances. Let us consider a set L containing M total numbers of elastic appliances, where $1 \leq m \leq M$. The power rating is denoted as ρ_{L_m} and each appliances is represented as $L_m \in L_M$. Each appliance has two parameters for operation, i.e., start time α_{L_m} and end time β_{L_m}. The total power consumption is symbolized by Γ_{ϕ}^{t} and given as:

$$\Gamma_{\phi}^{t} = \sum_{t=1}^{T} \sum_{L_m \in L_M} \lambda_{L_m}(\rho_{L_m}(t) x_{L_m}(t)). \tag{8}$$

where λ_{L_m} and $x_{L_m}(t)$ represents weather dependent factor and state of an appliance in a particular time slot t.

2) NON-INTERRUPTIBLE APPLIANCES

The operation time of such appliances is changeable, but once its operation is started then it cannot be interrupted until the completion of the task. Consider we have S_r set of non-interruptible appliances having ρ_{S_r} power rating of each appliance, and R ranges between $1 \leq r \leq R$. Each appliance has a start time α_{S_r}, stop time β_{S_r} and length of operation τ_{S_r} that is specified by the consumer. As the appliance start operation its energy consumption will be considered ρ_{S_r} otherwise it will be zero. The total power consumption of such appliances is given as:

$$\Gamma_{s}^{t} = \sum_{t=1}^{T} \sum_{S_r \in S_R} \rho_{S_r}(t) x_{S_r}(t)). \tag{9}$$

where $x_{S_r}(t)$ is the ON/OFF state of the each non-interruptible appliance in the current time slot t.

3) RECHARGEABLE APPLIANCES

These are portable appliances and the power utilization of these appliances during charging is in decreasing order. Consider set W containing R numbers of these appliances. The power rating of each appliance can be represented as ρ_{W_r}. For all the appliances, the consumer has defined the start time and stop time as:

$$\Gamma_{\omega}^{t} = \sum_{t=1}^{T} \sum_{W_r \in W_R} (\lambda_{W_R}(t) \rho_{W_r}(t) x_{W_r}(t)). \tag{10}$$

where $x_{W_r}(t)$ is the state of an appliance and λ_{W_R} represents the weight for power consumption that is high at the start of charging time t. Total power consumption by F shiftable appliances of a consumer is formulated below.

$$\Gamma_F^t = \Gamma_\phi^t + \Gamma_s^t + \Gamma_\omega^t. \quad (11)$$

The power consumed by the shiftable appliances must obey the following the constraint.

$$\Gamma^{min} \leq \Gamma_F^t \leq \Gamma^{max} \quad (12)$$

Constraint (11) ensures that the energy consumption of shiftable appliances Γ_F^t must be within the lower Γ_v^{min} and upper Γ_v^{max} limit defined for energy consumption by the controller.

C. SOLAR ENERGY SOURCE

Naturally available RES include solar energy, fuel cell energy, wind energy, biogas energy, tidal energy, etc. Among RES, solar energy is free (small operation and maintenance cost), abundant, and available in access of all consumers. In this study, solar energy source is equipped with houses and power grids. The goal is to minimize electricity cost, alleviate PAR, and mitigate carbon emission by effectively utilization of solar energy. The output power of solar energy system is determined by the following equation as [14]:

$$P^{pv}(t) = \eta^{pv} \times A^{pv} \times Irr(t) \times (1 - 0.005(Temp(t) - 25)) \quad (13)$$

where P^{pv} is the power generated by solar panels on hourly basis, terms η^{pv} and A^{pv} represent the efficiency and area of the solar panel, respectively. Outside environment temperature and solar irradiance are denoted by $Temp$ and I_{rr} respectively for the specific time of interval, 0.005 is the temperature correction factor.

The distribution of solar irradiation for an hour usually observe with a bi-modal distribution, which is a linear blend function of two uni-modal distributions. The uni-modal distribution is modeled using Weibull probability density function which is illustrated in Eq. (14)

$$F\,(Irr\,(t)) = \omega \left(\frac{\psi 1}{\lambda 1}\right)\left(\frac{Irr\,(t)}{\lambda 1}\right)^{(\psi 1-1)e^{-\left(\frac{Irr}{\lambda 1}\right)^{\psi 1}}} + (1-\omega)\left(\frac{\psi 2}{\lambda 2}\right)\left(\frac{Irr\,(t)}{\lambda 2}\right)^{(\psi 2-1)e^{-\left(\frac{Irr}{\lambda 2}\right)^{\psi 2}}}, \quad 0 < Irr\,(t) < \infty\lambda 1 \quad (14)$$

where ω is weighted factor, $\psi 1$, $\psi 2$ are the shape factors and $\lambda 1$, $\lambda 2$ are the scale factors.

D. BATTERIES STORAGE SYSTEM

This study considers batteries as an ESS. The batteries are equipped with solar energy system used to store solar energy when energy is surplus or off-peak hours, or battery charging level is below than lower cutoff. We have considered that the smart home is provided with a 3 kWh storage capacity. It has different constraint for charging such as minimum and maximum charging represented by ESS_{min} and ESS_{max}. Also, it has a specific limit of discharging to keep it safe and value of discharging is taken 90%. The storing energy equation is modeled as [14]:

$$SE(t) = SE(t-1) + k.\eta^{ESS}.ES^{ch}(t) - k.\frac{ES^{dis}(t)}{\eta^{ESS}}, \quad (15)$$

subject to:

$$ES^{ch}(t) \leq ES_{max}, \quad (16)$$
$$ES^{ch}(t) < ES_{upt}, \quad (17)$$
$$ES^{dis}(t) \geq ES_{min}. \quad (18)$$

where $ES_{ch}(t)$ is the charging state, $ES_{dis}(t)$ is the discharging state and ES shows the energy stored at interval time t, η^{ESS} indicates the efficiency of the batteries at interval time t.

E. DESIRED OBJECTIVES FUNCTION

This section describes the desired objectives function, which is modeled in Eq. (19). The objective function is dependent on the minimum energy cost, PAR, and the constraints given in Eqs. (20) to (26). The objective function is given below:

$$min \sum_{t=1}^{T} (\zeta(t) + \delta(t) + \theta(t)) \quad (19)$$

Subject to :

$$E(t) = P^{pv}(t) \quad (20)$$
$$\Gamma_v^t(t) + \Gamma_F^t(t) = (E(t) + ESS(t) + \phi(t)) \quad (21)$$
$$\sum_{a=1}^{n} \eta = LOT(a) \quad (22)$$
$$\sum_{a=1}^{n} \alpha \leq \eta \leq \beta \quad (23)$$
$$\phi_t \leq KI \quad (24)$$
$$0 < ESS_{min} < ESS_{max}, \quad \forall t \in T, \quad (25)$$
$$0 < Irr(t) < K_C, \quad \forall t \in T. \quad (26)$$

F. ELECTRICITY COST

In this section, we determined per unit energy price that changes in each time interval t. We used RTP tariff to estimate energy cost. Hourly energy cost is calculated by:

$$\zeta(t) = (\Gamma_v(t) + \Gamma_F(t)) \times EP(t). \quad (27)$$

where Γ_v^t and Γ_{sh}^t represent the energy consumption of fixed and shiftable appliances, respectively. Per day electricity cost can be calculated as:

$$\zeta(T) = \sum_{t=1}^{T} (\Gamma_v^t(T) + \Gamma_F^t(T)) \times EP(t). \quad (28)$$

Eq. (29) expresses the imported electricity from RES and ESS.

$$\phi(t) = (\Gamma_{ns}(t) + \Gamma_{sh}(t)) - (E(t) + ESS.\alpha_{ess}(t)).$$
$$\phi(t) = \begin{cases} \phi(t), & \text{if } \phi(t) \geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{29}$$

The total amount of imported energy is expressed in Eq. (32)

$$\phi(T) = \sum_{t=1}^{T} \phi(t) \tag{30}$$
$$\delta(t) = \phi(t) \times EP(t) \tag{31}$$
$$\delta(T) = \sum_{t=1}^{T} (\phi(t) \times EP(t)) \tag{32}$$

G. PAR

It is the ratio of the maximum load of consumer at time t to the mean load consumed during the schedule time. PAR shows the direct relationship between the consumers peak energy consumption and the EUCs peak power plants. To minimize PAR, it will be beneficial for EUCs to operate less number of peak power plants and consumers will get continuous power supply. Eq. (33) calculates PAR for N numbers of consumers.

$$\delta(T) = \frac{max(E_{total}(t))}{\frac{1}{T}\sum_{n=1}^{N}\left(\sum_{t=1}^{N} E_{total}(t, n)\right)} \tag{33}$$

H. CARBON EMISSION

Eq. (34) shows the carbon emitted from electricity consumption [43]. Where EP_{avg}, η, γ and m denotes the mean amount of bill per month for consumed energy, price per kWh that is equal 0.20 dollars, electricity emission factor equivalent of 1.37 and number of months in a year respectively.

$$\theta(t) = \frac{EP_{avg}}{\eta \times \gamma \times m} \tag{34}$$

I. USER COMFORT

In this paper, UC is related with electricity cost and waiting time of an appliance over scheduled horizon. Actually UC can be determined in terms of waiting time, it means that how long a user will have to wait for turning on the given appliance. To get lower electricity cost, the user has to operate their appliances according to schedule created by the proposed technique. We can calculate UC by the following equation:

$$Delay = \frac{\sum | Unschd(t) - Schd(t) |}{\sum(Schd(t))} \tag{35}$$

IV. PROPOSED HGAC OPTIMIZATION ALGORITHM FOR DSM

The HGAC optimization algorithm is obtained by cascading GA [41] and ACO [42] techniques. The developed HGAC optimization algorithm is devised by take complete steps of ACO technique, and the crossover and mutation steps of GA. The above stated techniques from the class of meta-heuristic techniques are chosen due to ACO Superior performance in aspects of electricity cost reduction and user comfort maximization, and in contrast, the GA is effective in aspects of PAR alleviation. Thus, key operators of ACO and GA are fused in HGAC optimization algorithm to schedule power usage of consumers to achieve electricity cost reduction, PAR alleviation, and user discomfort minimization. The HGAC optimization algorithm comprises of three stages: (a) complete steps of ACO algorithm, (b) crossover, and (c) mutation. The complete working of HGAC optimization algorithm is depicted in Figure 4. The parameters of the HGAC optimization algorithm are listed in Table 3. The superior performance of the HGAC optimization technique is because of: (a) deep layers structure, and (b) large controling parameters than the benchmark techniques. The state solid reasons (a) and (b) make HGAC optimization algorithm capable simultaneously achieve the desired objectives. However, due to reasons (a) and (b), it has more time complexity than existing techniques due to tradeoff int their behavior. The evaluation of the proposed and existing algorithms in terms of convergence rate, computational time, and complexity are listed in Table 2.

TABLE 1. HGAC optimization algorithm parameters.

Algorithm	Parameters	Values
HGAC	Number of iterations	200
	Population size	200
	antsh	10
	evaph	0.5
	insiteh	2
	Decision variable	1
	P_m	0.1
	P_c	0.9
	N	11

V. SIMULATION AND RESULTS

This section shows the simulation and results of our presented HEMS. We considered three cases: EUCs without RES and ESS, EUCs with RES, and EUCs with RES and ESS, to evaluate the behavior of proposed and existing algorithms (PSO, GA, WDO, ACO, and HGAC). Furthermore, the parameters of the proposed and existing algorithms are kept same subjected to fair comparison as listed in Table 3.

In the first case, we have taken the results considering EUCs without RES and ESS. Similarly, in the 2nd case EUCs with only RES is considered and in the third case EUCs with both the RES and ESS are integrated in terms of electricity cost reduction, PAR minimization, carbon emission reduction and UC maximization. The comparison of these three cases are illustrated in sections I, II and III. For simulations, we used MATLAB 2018a installed on Intel(R) Core(TM) m3-7Y30 CPU@ 1.60GHz and 8GB RAM. In our proposed model, we considered a consumer having 6 smart appliances that are connected with EMC via Wi-Fi. The EMC create schedule for each appliance according to electricity tariff. We designed a forecasting model for solar energy prediction to ensure more efficient energy management. The exogenous signals like load, temperature, solar irradiance, and RTPDR are forecasted using ANN, which are shown in Figures 5, 6, 7,

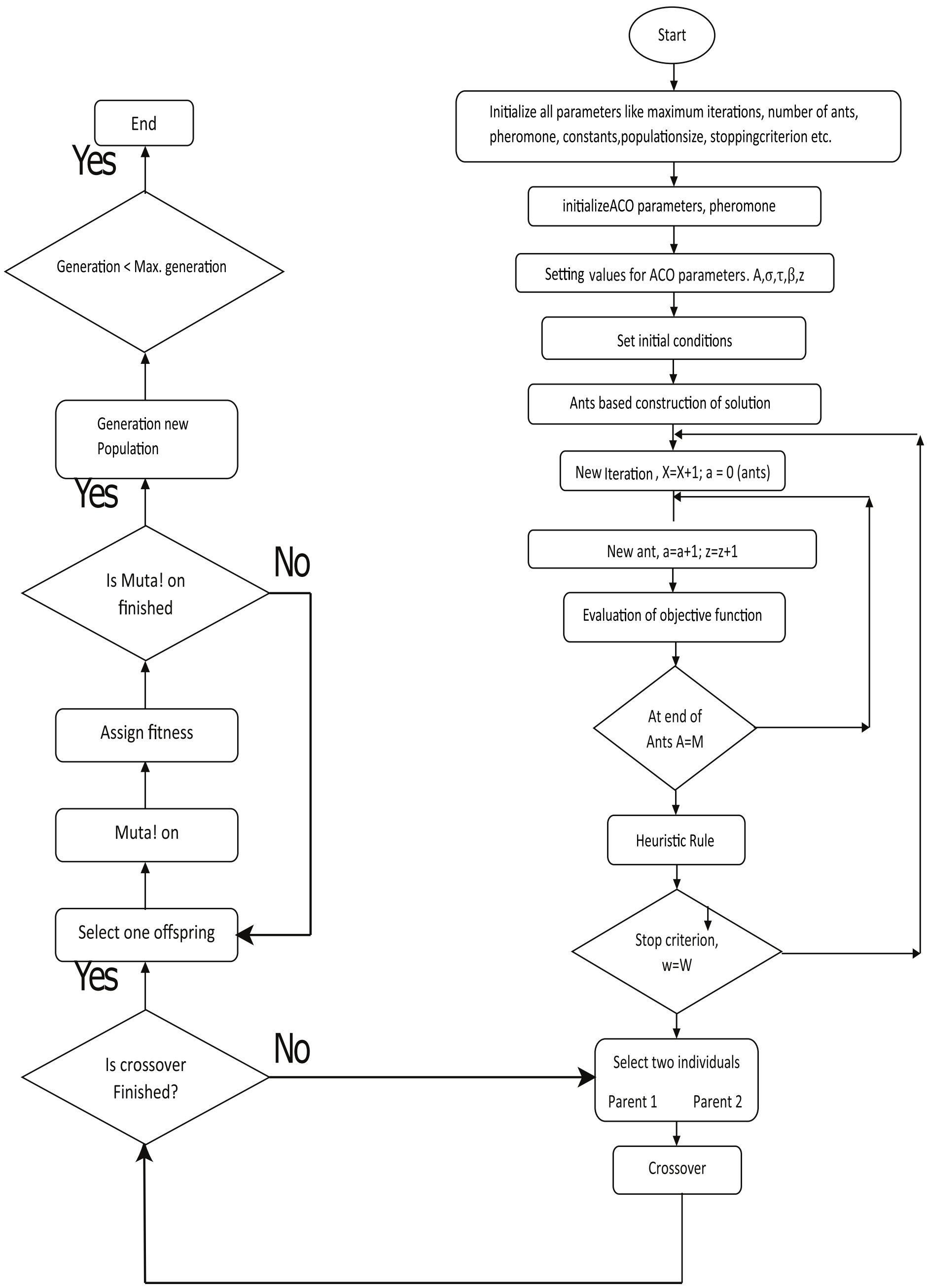

FIGURE 4. HGAC optimization algorithm for DSM using RTPDR.

TABLE 2. Proposed HGAC optimization algorithm and existing algorithms evaluation in terms of convergence rate, computational time, and complexity.

Algorithms	Iterations	Convergence	Computational time	Computational complexity
PSO	200	180	40 sec	High
GA	200	160	34 sec	High
WDO	200	140	32 sec	Medium
ACO	200	125	30 sec	Low
HGAC	200	120	27 sec	Medium

and 8, respectively [20]. The load pattern depicted in Figure 5 is the energy consumption profile of a smart home having three types load: elastic, non-interruptible, and rechargeable, which is forecasted using ANN. It is obvious that forecasted load closely follow the target load curve reveals the prediction is accurate. Figures 6 and 7 are the forecasted temperature and solar irradiance profile of METEONORM 6.1 of Islamabad region of Pakistan used for the generation of electricity. The

TABLE 3. Proposed and existing 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
	RT	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
HGAC	Number of iterations	200
	Population size	200
	antsh	10
	evaph	0.5
	insiteh	2
	Decision variable	1
	P_m	0.1
	P_c	0.9
	N	11

RTP signal shown in Figure 8 is defined by utility operator for DSM. The PV, the generated energy depends on the area of the solar panels, the conversion efficiency of the panels, solar irradiance, and ambient temperature.

We considered 90% of renewable energy for consumption during scheduling time horizon. The remaining 10% is assumed to provide the difference between the predicted and the target generation. Furthermore, the 30% of the predicted renewable energy is utilized for the charging of ESS when its charging level is between 10-90%. Figures 9 and 10 illustrate the charging level of ESS and predicted renewable energy, profile of RE after 10% uncertainty and after charging the ESS, respectively.

A. CASE 1

In this case, we considered a consumer using electricity of EUCs without RES and ESS integration. We scheduled the user load by using the heuristic algorithms that are proposed in our scheme, and compared the results with unscheduled load in terms of electricity cost, PAR and carbon emission. That are discussed in details in the subsequent sections.

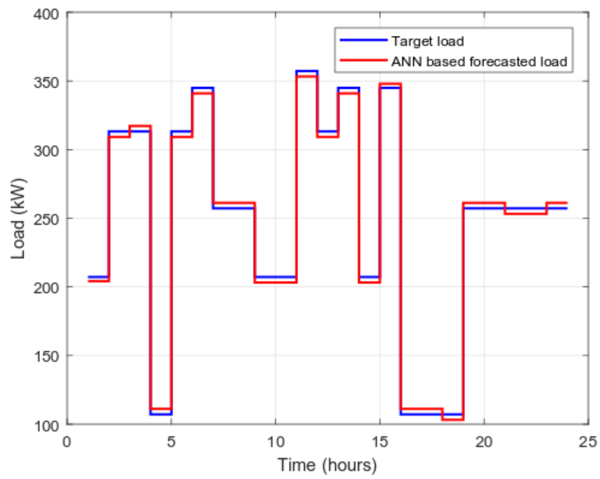

FIGURE 5. Residential consumers load profile.

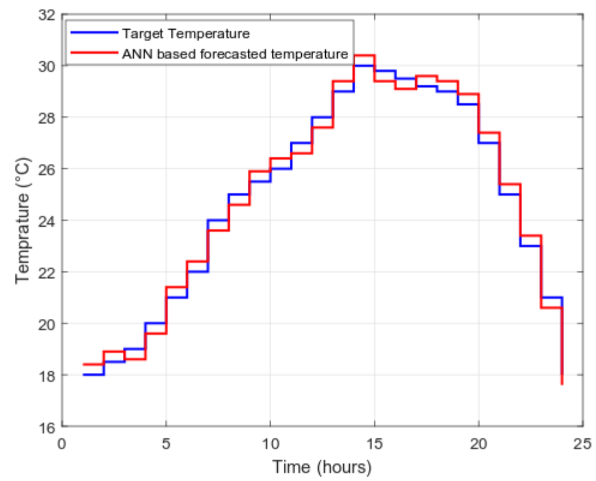

FIGURE 6. Forecasted ambient temperature.

1) ELECTRICITY COST

Figure 11 illustrates cost of electricity consumed by load with and without scheduling for first case considered. In case of unscheduled load, the maximum cost is 70 cents in time slots 9-10, PSO scheduled load has electricity cost of 65 cents in time slot 19, 21, and 23, for GA the maximum cost is 50 cents at 9 time slot. Similarly, the WDO maximum cost of energy consumed is 54 cents in time slot 9, the ACO has 48 cents cost in time slot 9, while the proposed HGAC the maximum cost is 53 cents in hours 19, 21, and 23. By summing up per day electricity cost of unscheduled and scheduled loads of PSO, GA, WDO, ACO and HGAC is 777, 680, 729, 734, 701 and 690 cents respectively. From the results, it is shown that PSO has the reduction of 11.55%, in case of GA cost is reduced by 6.27%, WDO based load has reduced the overall cost by 5.51%, in case of ACO cost is reduced by 9.78%, while of the proposed HGAC the electricity cost 12.16% reduction. So it is clear that our proposed algorithm has efficiently scheduled the overall load as compared to the existing algorithms.

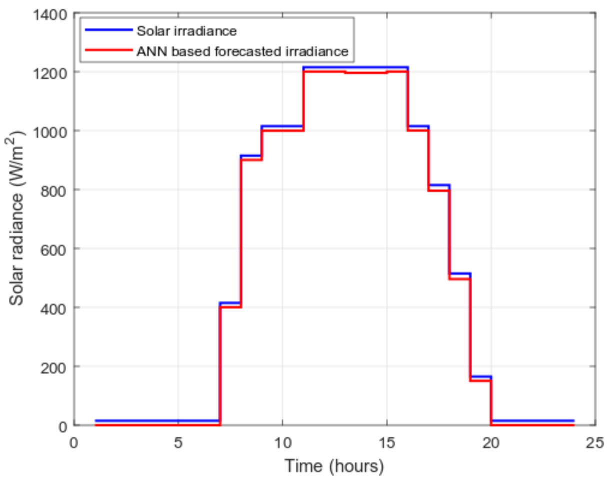

FIGURE 7. Solar irradiance.

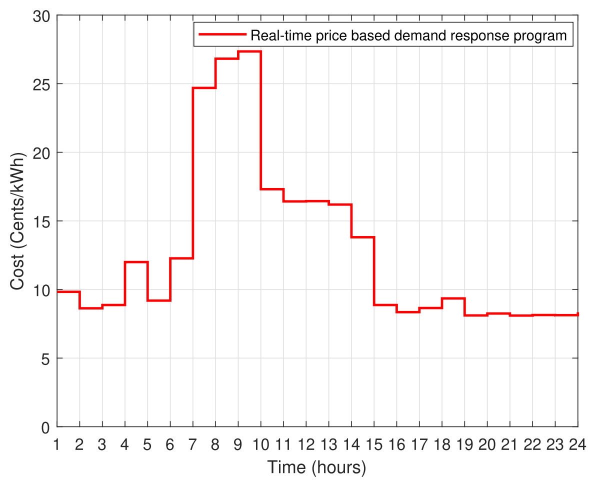

FIGURE 8. Real-time price based demand response program.

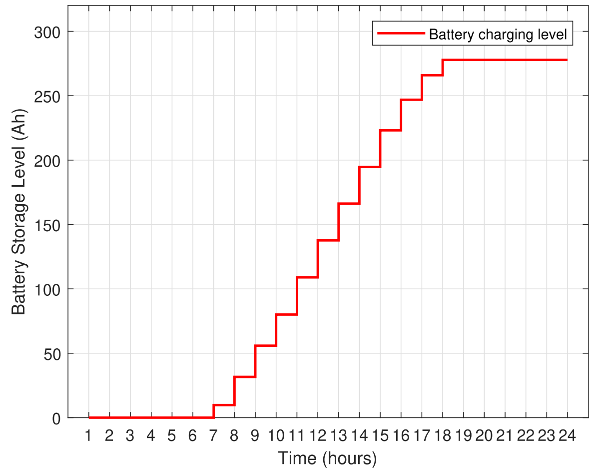

FIGURE 9. Battery charging level.

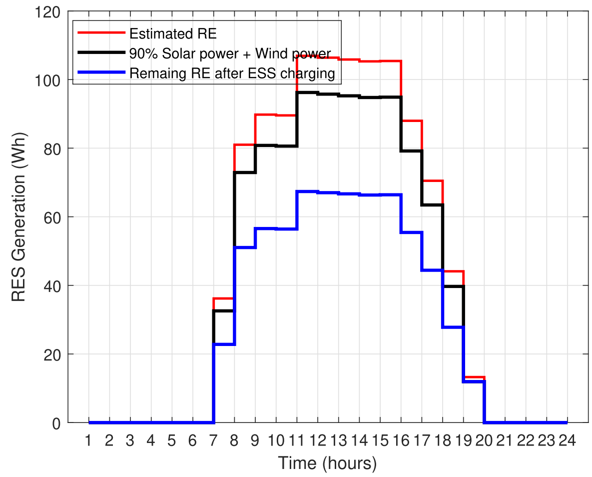

FIGURE 10. Estimation of RES for optimal utilization.

2) PAR

Figure 12 shows the PAR of unscheduled and scheduled loads when RES and ESS are not integrated with EUCs. From the results, it is clear that HGAC optimization algorithm has maximum reduction of 19.44%, while in case of PSO, GA, WDO and ACO the reduction in PAR is 5.55%, 8.33%, 2.74% and 13.8%, respectively. These algorithms are supposed to minimize the overall load but the PSO shifted more load to low price hours which creates rebound peaks. These new peaks in turn create instability in the power system and as a result EUCs imposes penalty on the consumers. Though the ACO and HGAC algorithms uniformly distribute the overall power demand of load, and results low PAR.

3) CARBON EMISSION

Figure 13 shows the carbon emission of unscheduled and scheduled loads without the integration of RES and ESS. The maximum carbon emitted in case unscheduled load is 150 pounds in time slot 21, the PSO has 142 pounds in time slot 21, GA has 147 pounds carbon emission in time slot 21, in case of WDO it is 138 in hour 21, the ACO has 147 pounds hour 21, while the proposed HGAC optimization algorithm the maximum carbon emission is 144 pounds in hour 21. Results illustrate that the proposed algorithms have significantly reduced the carbon emission as compared to ACO, GA, and unscheduled case. In case of PSO, reduction occurred by 5.4%, in case of GA it is 2.08%, in case of WDO it is 8.05%, ACO scheduled load has reduced carbon emission by 5.4%, while in case of the proposed HGAC algorithm it is 4.00%. It is clear that our proposed algorithm has the maximum reduction of carbon emission as compared to ACO, GA, and unscheduled case, and low reduction than PSO and WDO.

4) USER COMFORT

The proposed HGAC optimization algorithm created schedule is compared with existing algorithms created schedule for the purpose to evaluate UC in aspects of waiting or delay time that posed to the consumers. The UC in terms of waiting or delay time evaluation of created schedule using the proposed HGAC algorithm compared to existing algorithms are depicted in Figure 14. The complete discussion with solid reasoning is as given below. In GA created schedule average delays of 0, 0.8, 1.2, 0, 0 and 1 hour are faced by water heater, refrigerator, clothes dryer, lights, washing machines,

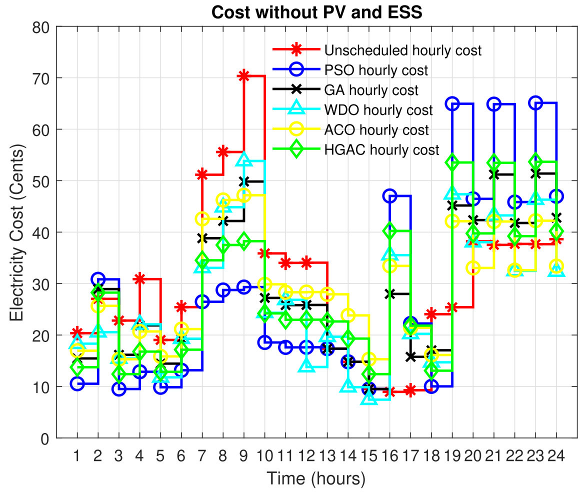

FIGURE 11. Cost reduction in case 1.

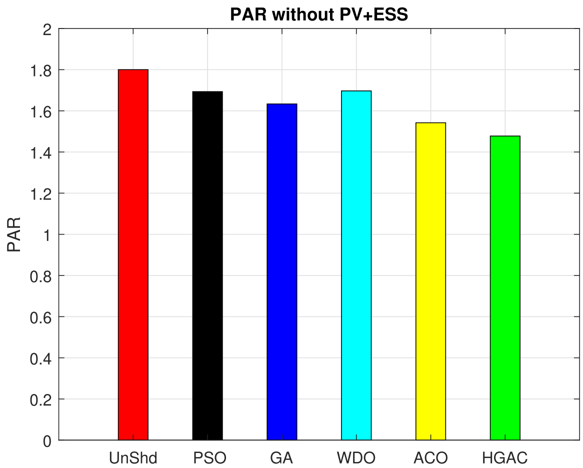

FIGURE 12. PAR reduction in case 1.

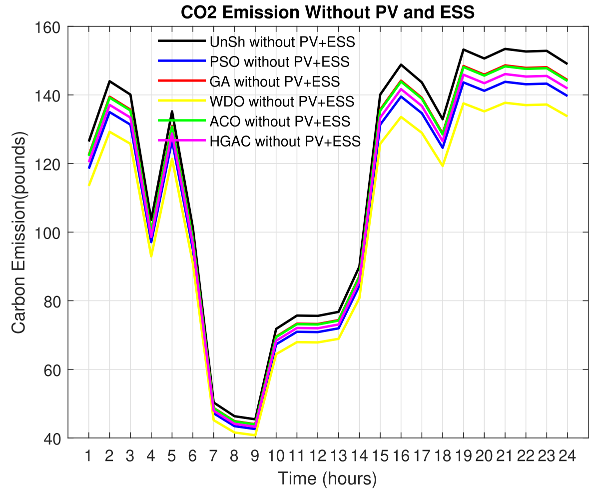

FIGURE 13. CO_2 emission in case 1.

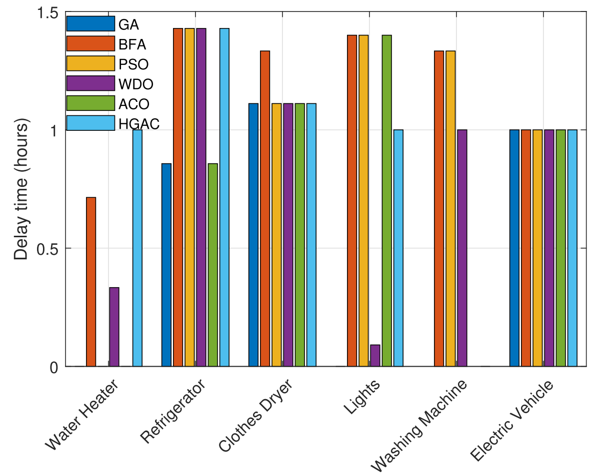

FIGURE 14. UC in case 1.

and electric vehicles, respectively, as depicted in Figure 14. Similarly, ACO created schedule average delays of 0, 0.8, 1.2, 1.4, 0 and 1 hour are faced by water heater, refrigerator, clothes dryer, lights, washing machines, and electric vehicles, respectively. The proposed HGAC optimization algorithm created schedule has average delays of 1, 1.4, 1.2, 1, 0 and 1 hour are faced by water heater, refrigerator, clothes dryer, lights, washing machines, and electric vehicles, respectively. The delay of HGAC optimization algorithm is high for some appliances due to the existence of tradeoff in nature.

B. CASE 2

In this case, the consumers are considered only with integrated RES. We scheduled the user load by using the heuristic algorithms that are proposed in our scheme, and compared the results with unscheduled load in terms of electricity cost, PAR and carbon emission. The results in terms of each objectives are discussed in the subsequent sections.

1) ELECTRICITY COST

Figure 15 illustrates the electricity costs of unscheduled and scheduled load when only RES are integrated with EUCs. Results show that the proposed HGAC optimization algorithm compared to existing algorithms (PSO, GA, WDO, ACO) have significantly minimized the overall cost. In Figure 15 the maximum electricity cost in case of unscheduled load is 92 cents in hour 9, the PSO it is 41 cents in hour 2, in case of GA the maximum cost is 51 cents in hour 9, similarly the WDO it is 49 cents at 21 and 23 time slots, the ACO it is 38 cents at 7 time slot, while in the case HGAC it is 33 cents at time slot 2. The overall per day electricity costs by unscheduled load, PSO, GA, WDO, ACO, and HGAC scheduled loads are 684, 532, 593, 610, 547, and 501 cents, respectively. From the results, it is clear that our proposed algorithm HGAC has significantly reduced the overall electricity cost by 26.8%, while the PSO, GA, WDO and ACO the overall reduction in cost is 20.02%, 13.3%, 10.8% and 22.22%,, respectively. This show that our proposed HGAC heuristic algorithm has efficiently reduced the electricity bills as compared to existing algorithms.

2) PAR

Figures 16 shows the PAR of the unscheduled and scheduled loads with integrated RES. From the results, it is clear that the proposed heuristic algorithms have reduced the overall load on the gird. In case of PSO, reduction is 12.5%, the GA it

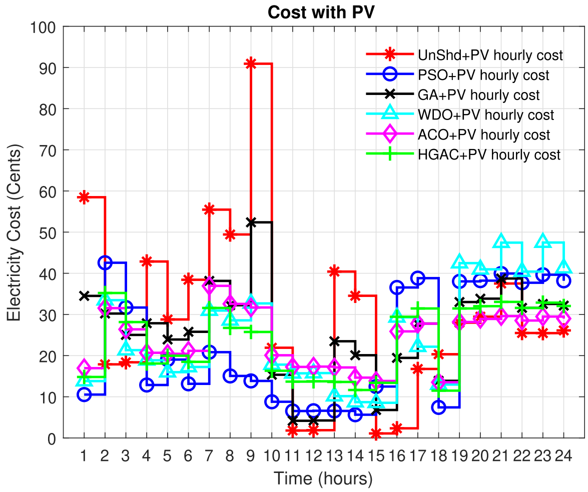

FIGURE 15. Cost reduction in case 2.

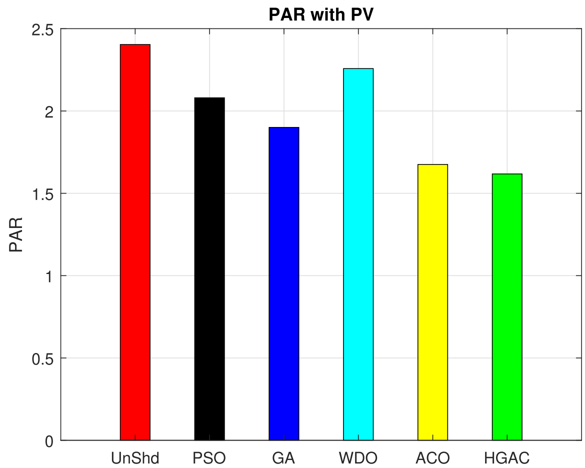

FIGURE 16. PAR reduction in case 2.

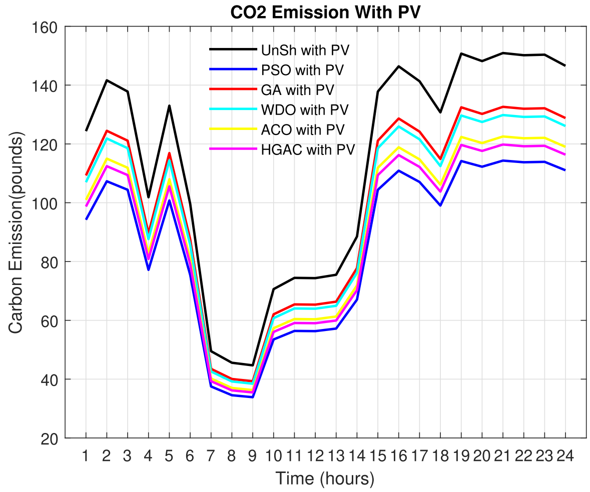

FIGURE 17. Carbon emission in case 2.

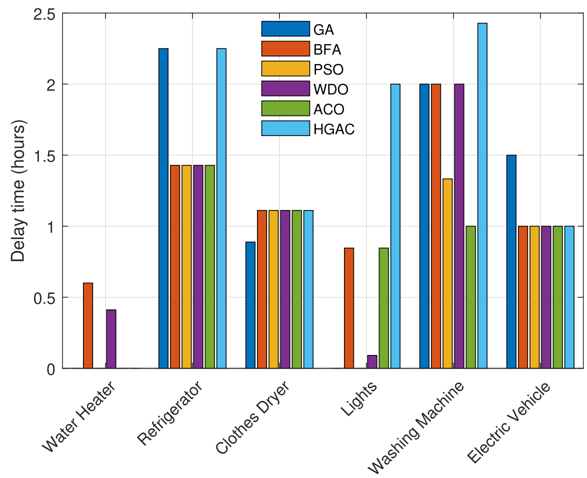

FIGURE 18. UC in case 2.

is 20.83%, WDO has reduced PAR by 4.1%, similarly, ACO has 29.16% reduction, while HGAC has reduced it by 33.3%. WDO has shifted most of the load to off-peak hours results rebound peaks due to which the EUCs impose a penalty on the consumer. However, rest of the algorithms distribute their load over scheduling time horizon uniformly to achieve desired outputs.

3) CARBON EMISSION

Figure 17 illustrates carbon emission unscheduled and scheduled loads using proposed heuristic algorithms when RES is integrated with EUCs. In case of unscheduled load, the maximum carbon emission is 150 pounds in hour 19, similarly in case of PSO the maximum carbon emission in time slot 21 is 115 pounds, the GA, it is 135 pounds in time slot 21, WDO based scheduled load has maximum carbon emission of 132 pounds in time slot 19. In case of ACO, it is 122 pounds in time slot 19, while HGAC has 120 pounds carbon emission in time slot 19. Results shows that the proposed algorithms have significantly reduced the carbon emission as compared with carbon emitted by unscheduled load. Per day carbon emitted by unscheduled, PSO, GA, WDO, ACO and HGAC based loads is 2604, 2024, 2256, 2320, 2082 and 1908 pounds, respectively. The percentile reductions by PSO, GA, WDO, ACO and HGAC are 23.28%, 13.35%, 10.92%, 20.06% and 20.71%, respectively. It shows that our proposed hybrid has more reduction in carbon emission as compared to GA, WDO, ACO, and unscheduled case while low carbon reduction compared to PSO.

4) USER COMFORT

The proposed HGAC algorithm created schedule is compared with existing algorithms created schedule for the purpose to evaluate UC in terms of waiting or delay time that posed to the consumers. The UC in terms of waiting or delay time evaluation of created schedule using the proposed HGAC algorithm compared to existing algorithms are shown in Figure 18. The complete discussion is given as follows. In GA created schedule average delays of 0, 1.4, 0.8, 0, 2, and 1.5 hour are faced by water heater, refrigerator, clothes dryer, lights, washing machines, and electric vehicles, respectively, as depicted in Figure 18. Similarly, ACO created schedule average delays of 0, 2.3, 1.2, 0.8, 1 and 1 hour are faced by water heater, refrigerator, clothes dryer, lights, washing machines, and electric vehicles, respectively. The proposed HGAC optimization algorithm created schedule has average

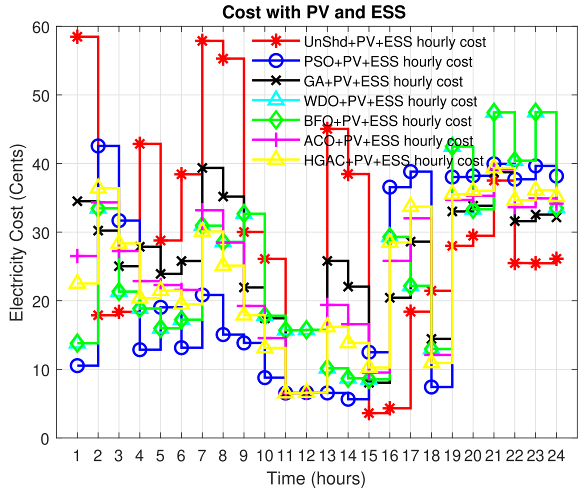

FIGURE 19. Cost reduction in case 3.

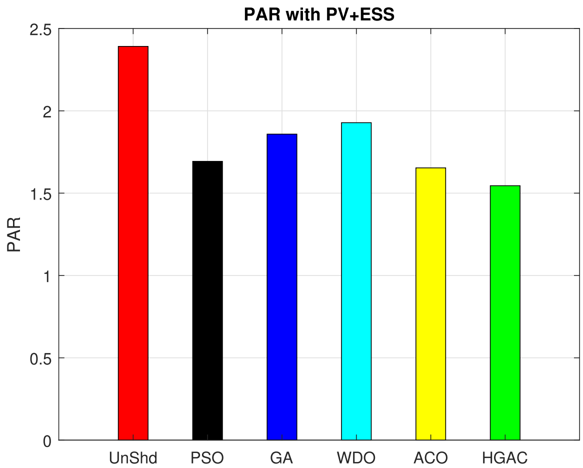

FIGURE 20. PAR reduction in case 3.

delays of 0, 2.3, 1.2, 2, 2.4, and 1 hour are faced by water heater, refrigerator, clothes dryer, lights, washing machines, and electric vehicles, respectively. The delay of HGAC optimization algorithm is high for some appliances due to the existence of tradeoff in nature.

C. CASE 3

In this case, we have integrated RES along with ESS with EUCs. We scheduled the user load by using the heuristic algorithms that are proposed in our scheme, and compared the results with unscheduled load in terms of electricity consumption bills, PAR and carbon emission. The complete discussion is given as follows.

1) ELECTRICITY COST

The electricity cost with integrated RES and ESS is represented in Figure 19. In case of unscheduled load, the maximum cost is 59 cents in time slots 1, 7, 8 similarly the PSO it is 42 cents in hour 2, 3, GA based consumption has 39 cents maximum electricity cost in hour 7, 8, WDO based load has increased maximum electricity cost to 48 cents in hour 21, 22, 23, and 24, the ACO maximum electricity cost is 38 cents in hour 21, while the HGAC it is 38 cents in hour 21. The

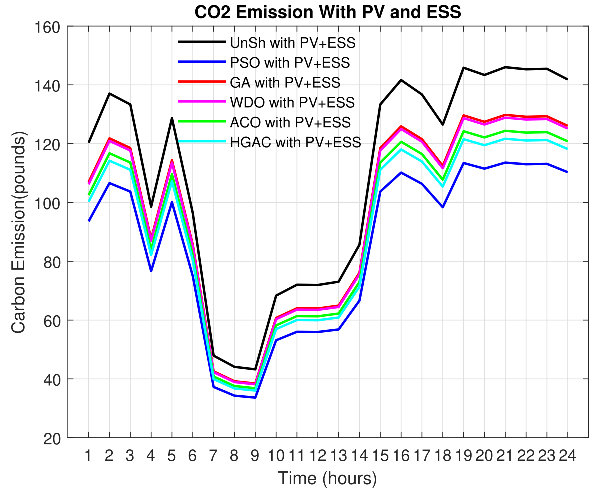

FIGURE 21. Carbon emission reduction in case 3.

overall electricity costs per day of unscheduled, PSO, GA, WDO, ACO and HGAC based consumption's are 665, 501, 583, 570, 556, 542 cents, respectively. It is clear that our proposed algorithms have reduced the cost over the entire scheduled horizon as compared to unscheduled load. PSO has reduced the cost by 18.61%, the GA based consumption cost in reduction is 12.33%, WDO has reduced the electricity cost by 14.05%, similarly the ACO it is 16.39%, while HGAC has 24.40% reduction. From the results it is obvious that our proposed algorithm HGAC has efficient load management strategy that has significantly reduced the cost as compared to the existing heuristic algorithms.

2) PAR

Figure 20 illustrates the PAR of unscheduled and scheduled loads with RES and ESS. It shows that our proposed algorithm HGAC has 37.08% reduction in PAR. The PSO, GA, WDO and ACO the reductions in PAR are 29.16%, 25.03%, 20.83%, and 31.25%, respectively. It shows that the PSO and WDO shifts most load from high to low price hours that creates rebound peaks. Due to these new peaks the whole operation time of peak plants will be disturbed and also the EUCs will impose a penalty on the consumer. However, ACO and HGAC distribute load uniformly over the entire scheduled time horizon to achieve desired objectives. Thus, HGAC outperforms existing algorithms in terms of PAR.

3) CARBON EMISSION

The carbon emission of unscheduled and scheduled loads with REs and ESS are presented in Figure 21. The maximum carbon emitted by unscheduled electricity consumption is 142 pounds in time slots 19, 21 and 23, the PSO, the maximum carbon emission is 115 pounds in hour 19, GA based consumption has 125 pounds carbon emission in hours 19 and 21, WDO based consumption has emitted 125 pounds in hour 19, 21, the ACO it is 122 pounds in hour 21 and the HGAC it is 121 pounds in hour 21. Moreover, per day carbon emissions the unscheduled load, PSO, GA, WDO, ACO, HGAC based consumption are 2529, 1908, 2219, 2171, 2115, and

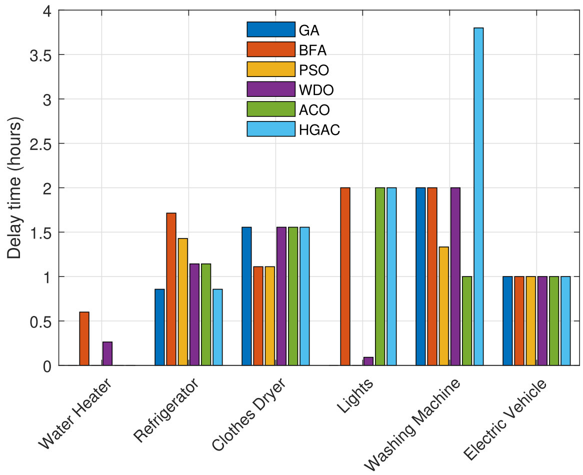

FIGURE 22. UC in case 3.

2064 pounds, respectively. From the results it is clear that maximum reduction of 21.93% has occurred in the case PSO. While the GA, WDO, ACO and HGAC is 10.96%, 11.05%, 14.62% and 16.44%, respectively. It is clear that HGAC has more reduction in carbon emission as compared with GA and ACO algorithms.

4) USER COMFORT

To curtail the electricity bills and PAR, we have shifted the loads to off-peak hours, where electricity per unit charge is at minimum price and also load decreases on the grids. Due to this shifting consumers appliances face average delay or waiting time which directly affects the UC. We considered UC as the average delay of the appliance; if the average delay of an appliance is high it corresponds to reduced UC. This means that UC and average delay of an appliance are inversely proportional to each other. PAR reduction does not affect the UC, however, electricity cost affects UC and there is a tradeoff between them. To reduce the electricity bills the average delay of the appliances will increase and as a result, the UC will decrease. Therefore, the consumer has to compromise on his comfort to reduce the electricity bills. Figure 22 represents the average delay of BPSO, GA, WDO, ACO, and HGAC algorithms, respectively. Results show that BPSO has less average delay for lights but large average delay for washing machine as compared to other heuristic algorithms. Moreover, our proposed algorithm HGAC has significantly decreased the average delay of all the appliances as compared to the parent algorithms GA and ACO. As a result HGAC has increased the UC efficiently as compared with all the other algorithms.

VI. CONCLUSION

The implementation of real-time price-based demand response program and integration of renewable energy resources (RESs) improves efficiency and ensure power system stability of electric grid. This paper introduces a DSM framework in SG integrated with RES to adapts energy usage behavior of consumers in response of RTPDRP to create operation schedule. Then, the HGAC optimization algorithm is developed, which is a hybrid of ACO and GA. The HGAC optimization algorithm solve the complete scheduling problem for three cases: EUCs without RESs, EUCs with RESs, and EUCs with both RESs and storage technologies. The consumers using the created schedule for three cases minimize energy cost, peak load, carbon emission subjected to improving user comfort and avoiding rebound peaks. To validate the HGAC optimization algorithm based DSM framework simulations are conducted and the proposed model is compared with existing frameworks like ACO, PSO, GA, and WDO algorithms. Simulation results and discussion reveals that the proposed HGAC optimization algorithm reduced electricity cost, carbon emission, and peak load by 12.16%, 4.00%, and 19.44% in case I; by 26.8%, 20.71%, and 33.3% in case II; and by 24.4%, 16.44%, and 37.08% in case III, respectively, compared to without scheduling. In the future, we will devise a decentralized framework of multimicrogrids, where environment friendly energy will be provided to consumers on demand. The energy allocation will be formulated as Stackelberg game and adapt backward induction to optimize the profit of bmicrogrids and consumers.

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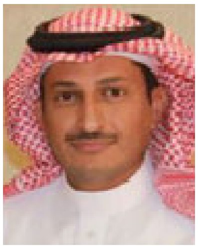

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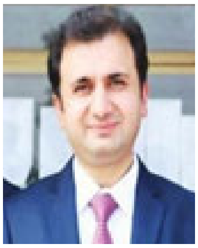

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