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Hybrid optimization approach for power scheduling with PV-battery system in smart grids

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ABSTRACT

This manuscript proposes a hybrid method for the smart-grid (SG) optimization, which combines automatic demand-response (DR) shedding with load classification. The integration of the Mexican Axolotl Optimization (MAO) and Honey Badger Algorithm (HBA) constitutes the proposed hybrid approach. The HBA method improves the axolotls' updating behavior. It is commonly referred to as the Enhanced MAO (EMAO) approach. The proposed energy-management framework optimizes customer power consumption patterns to minimize carbon-emissions, electricity-costs, and peak-power-consumption. By integrating utility generation, PV-battery systems, and dynamic price signals using the EMAO approach, it reduces power consumption costs, minimizes peak-fluctuations, and lowers carbon emissions. The EMAO control-topology is rigorously evaluated through MATLAB simulations, demonstrating superior performance compared to existing optimization methods such as HGPO, PSO, and GA. The results showcase the EMAO algorithm consistently achieving the lowest cost at 310 cents, minimizing carbon emissions to 1.8 pounds, and achieving a high load classification accuracy of 98.2 %. With a moderate performance-to-cost ratio of 1.7, the EMAO algorithm excels in energy management, effectively balancing cost considerations, environmental impact, and load classification objectives. The proposed hybrid method effectively integrates DR shedding and load classification to optimize SG-operation, achieving significant improvements in cost, emissions, and load-classification accuracy compared to traditional methods.

1. Introduction

Electrical energy is an indispensable facet of modern human life, underpinning the functioning of societies, industries, and economies [1,2]. However, in many developing countries, the provision of reliable electricity remains a formidable challenge, primarily due to budget constraints and limited generating capacity [3,4]. The consequence of this shortfall often manifests as load shedding, a disruptive practice that frustrates consumers and hampers economic development [5,6]. In response to these pressing issues, Demand Side Management (DSM) emerges as a compelling solution, particularly when seamlessly integrated with the transformative capabilities of Smart Grid technology [7,8]. Furthermore, the environmental repercussions associated with conventional power generation methods have intensified the urgency to explore Renewable Energy Sources (RESs) as a promising and sustainable alternative [9,10]. Several works have earlier presented in the literature were based on load classification with automatic shedding of demand response in smart grid by utilizing various approaches and features. A few works were given below [11,12].

Daneshvar et al. [13], have suggested an efficient scheduling method for multi-energy hubs in the day-ahead market, aiming to cut energy hub costs and decrease greenhouse gas emissions. The approach relies on maximizing clean energy production from WTs and photovoltaic panels at each hub, minimizing gas-fired system operation. However, it faces challenges due to the unpredictable behavior of stochastic producers, necessitating scenario reduction for practical application. Jadidbonab et al. [14], have devised a solution to the issue of optimum scheduling of smart residential energy hubs (SREHs) while accounting for various unknown characteristics. A risk-constrained two-stage stochastic programming model was used to characterize the influence of market pricing, demand, and solar radiation uncertainties on the SREH scheduling issue. Daneshvar et al. [15], have presented a real-time energy market optimum energy dispatch scheduling model for renewable-based energy hubs. Battery energy storage methods, on the other hand, impose extra expenses and constraints. Mahto et al. [16], have studied the issue

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Nomenclature

DSM	Demand Side Management
RESs	Renewable Energy Sources
DR	Demand Response
EMS	Energy Management Systems
CSFs	Common Storage Facilities
GA	Genetic Algorithms
PSO	Particle Swarm Optimization
PAR	Peak to Average Ratio
RTP	Real-Time Pricing
RES	Renewable Energy Sources
AMI	Advanced Metering Infrastructure
EMC	Energy Management Controller
RAs	Regular Appliances
HGPSO	Hybrid Genetic Particle swarm Optimization
V_{th}	Thermal voltage of diode
I_{ph}	Photocurrent generated by the solar cell
I_{sh}-Shunt	current
T	Temperature in kelvin
Q	Elementary charge
r_{se}, r_{sh}	Series resistance, shunt resistance
μ^{ess}	Effectiveness of energy storage system
ee^{CH} and ee^{dCH}	the power supplied (Kw) from photovoltaic to energy storage system and ESS to load
d_{SHI}	Every appliance sold by sias
γ_{SHI}	On/off appliance status
e^{SHU}	Net energy consumption
$d_{SHU} \in A_s$	Each appliance from sias
γ_{SHU}	Status of the appliances' on/off
$AVGep$	Average electricity price
ς	Electrical emission factor
Φ_t	Energy consumed by the appliance at time T
$t_{B,T}^{0,UNSCH}$, $t_{B,T}^{0,UNSCH}$	The status of appliance without and with scheduling
ω_B^D	An appliance can experience maximum delay
i	Operating time of appliances and T_1 to T_{24} as time-slots
PEDs	Priced Elasticity Demands
PV	Photovoltaic
SREH	smart residential energy hub
DSP	distribution system planning
DLC	direct load control
SG	smart grid
MAO	Mexican Axolotl Optimization
HBA	Honey Badger Algorithm
ESS	Energy Storage System
EMAO	Enhanced Mexican Axolotl Optimization
MDMS	Meter Data Management System
DTR	delay-time-rate
SUAs	Shiftable Uninterruptible Appliances
SIAs	Shiftable Interruptible Appliances
v	Voltage across the cell
$V_{ter\ \min\ al}$	Terminal voltage of the cell
I_{out}	Output current of the solar cell
ps	Stored energy (kwh) at time T
n_P and n_S	number of modules attached in series and parallel
K	Boltzmann's constant
η	Duration of time in hours
e^{SHI}	Net energy-consumption
Ω_{SHI}	Power consumption of all appliances
β	The unit price
A_s	Sum of shiftable uninterruptible appliances
Ω_{SHU}	Power-consumption of all appliances
$\prod$	Shiftable interruptible and uninterruptible appliances of net electricity costs by consumers
$\in$	Cost per kwh
ζ	Number of hours in a day
ω_B	Communicates an appliance-specific delay time rate based on operational delays
t_B^{LO}	Length of net operation time-slots
t_B^T	As appliance of net time-interval

of power and energy management on the grid's consumption side via decision-making and load management based on the dynamic price of electricity. Ebrahimi and Ahmadi [17] have suggested a unique under-voltage load shedding strategy for power system voltage stability. Voltage-dependent load models and discrete load levels, on the other hand, impair the accuracy of load shedding strategies. Moradi-Sarvestani et al. [18], have presented distribution system planning (DSP) with demand response (DR), emphasizing direct load control (DLC) DR using financial incentives for consumers with smart meters and switches. However, integrating detailed demand response data may introduce inflexibility in distribution system design. Since more prosumers and renewable energy sources were being used, demand-side energy management must be incorporated for reliable and sustainable grid operation, according to Rehman et al., [19]. However, Lack of confidence among parties hinders the adoption and effectiveness of demand-side energy management.

The review of recent research shows that the load classification with automatic shedding of demand response in smart grid is the most challenging task. Uncertain behaviors of stochastic energy producers, like renewables, pose challenges in accurate energy scheduling. Overly conservative risk-constrained models may hinder the full utilization of renewable energy sources when actual uncertainties are lower than predicted. Integration of battery energy storage systems introduces constraints such as finite storage capacity and ongoing maintenance costs. Voltage-dependent load models may not accurately represent load behaviors, potentially leading to suboptimal load management. Additionally, computational intractability issues arise in distribution system planning with increasing prosumers and renewable sources. The above-mentioned limitations are motivated to do this research work.

Smart Grids use three approaches for optimal Demand Side Management (DSM): game theory-based strategies, heuristic algorithms, and mathematical methods. Each has strengths and challenges. Mathematical techniques offer robust tools but struggle with renewables and scale. Game theory balances comfort and cost but may miss complexities. Heuristic algorithms like PSO and GA prioritize DSM goals but need to consider grid resilience and user satisfaction. Challenges remain in handling renewables, ensuring comfort, and achieving grid sustainability. This study contributes to addressing these challenges in DSM.

Contribution and novelty.

- This study proposes a hybrid technique that combines automatic DR shedding with load classification techniques to improve energy management.
- This study introduces the Honey Badger Algorithm to enhance the MAO algorithm, improving the optimization process and power consumption scheduling.
- This study proposes an energy management framework based on optimization techniques that adapt customer power consumption patterns to minimize carbon emissions, electricity costs, and peak power consumption.

- The proposed EMAO algorithm is thoroughly evaluated through simulations conducted in MATLAB. It is compared with existing optimization methods, like Hybrid Genetic Particle Optimization (HGPO), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). The outcome shows that the superiority of the EMAO algorithm is based on cost reduction, carbon emissions, and performance-to-cost ratio.
- The proposed EMAO algorithm consistently achieves the lowest cost and lowest carbon emissions compared to existing optimization methods. It also maintains a moderate performance-to-cost ratio, highlighting its cost-effectiveness and efficiency in energy management.

The novelty of this study lies in the development of a hybrid technique that combines automatic demand response shedding with load classification techniques. The study also introduces the Enhanced MAO (EMAO) algorithm, which enhances the scheduling of power consumption. This novel approach improves energy-management in the smart-grid, resulting in cost reduction, carbon emission reduction, and optimized power consumption. The rest of the paper is described as follows: section 2 explains the structure of energy-management using smart grid, section 3 details the hybrid strategy, section 4 demonstrates the result and discussion, and section 5 concludes the paper.

2. Configuration of energy management in SG with photovoltaic-battery system

Fig. 1 depicts the structure of Energy management in SG. The proposed approach is incorporated with grid and smart meter, PV module, energy storage system (ESS), smart home appliances, and grid. To lessen the cost of electricity in this manuscript, a hybrid EMAO approach is proposed to lessen the energy management cost by using smart grid. The two way communication is utilized for managing and solving the issues of demand-side. For managing the energy, in this manuscript, the controller of energy management EMAO is proposed to schedule the load. User discomforts, Peak to average ratio (PAR), reduction of carbon emission, are the key goals of the proposed method [20].

2.1. PV modeling

A solar cell is an electrical device that converts light energy into electricity via the PV effect. To make an equal circuit diagram of a solar PV cell, connect the current source in parallel to an inverted diode with shunt and series resistances [21]. The shunt resistance contributes to

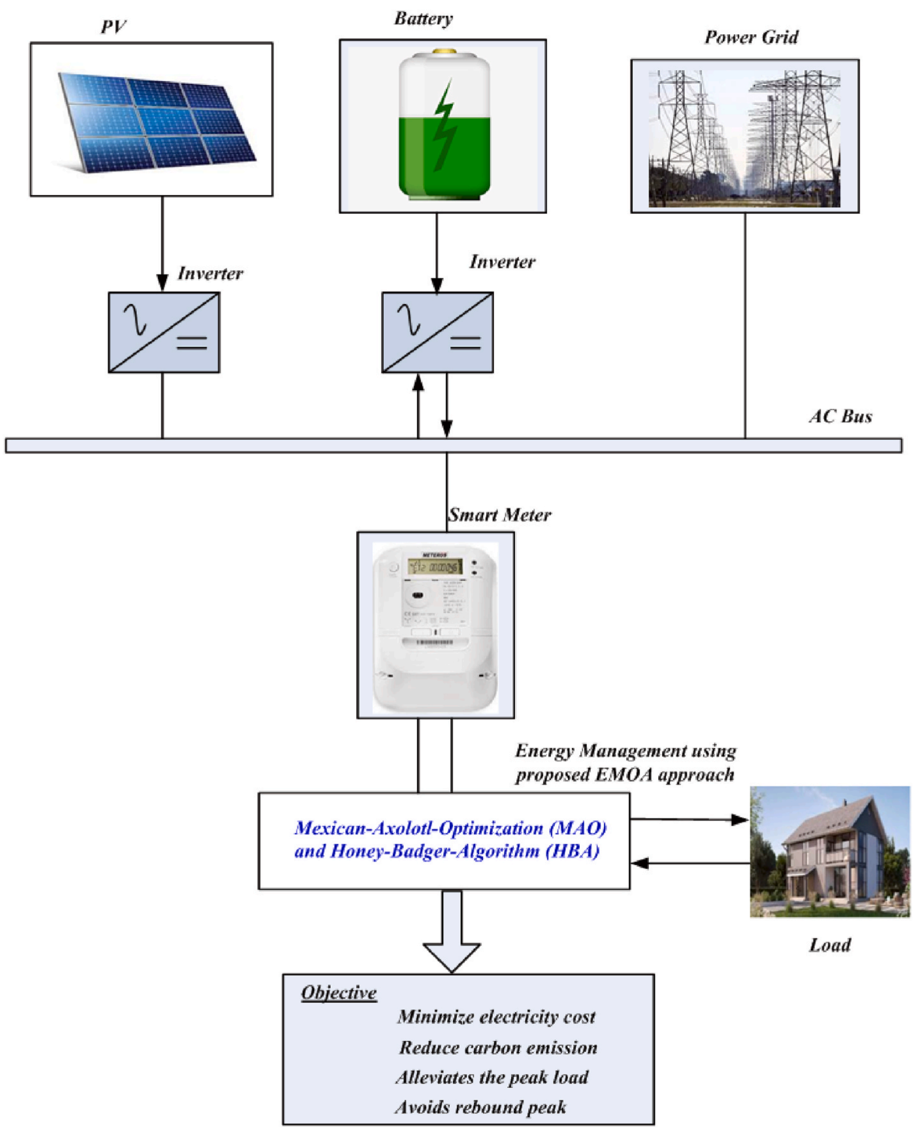

Fig. 1. Configuration of energy management in SG

leakage current; however, the series resistance obstructs electron passage from the N to P junction. When a PV cell receives solar irradiation, the output current is represented as,

$$I_{out} = n_p I_{ph} - n_p I_1 \left[e^{\frac{\left(\frac{v}{n_s} \times I_{out} \times \frac{r_s}{n_p}\right)}{n + V_{ter\min al}}} - 1 \right] - I_{sh} \tag{1}$$

where I_{out} denotes the output current of the solar cell, I_{ph} indicates Photocurrent generated by the solar cell, v is the voltage across the cell, $V_{ter\min al}$ is the terminal voltage of the cell, I_{sh} indicates the Shunt-current. The thermal-voltage of diode is

$$V_{th} = \frac{K \times T}{Q} \tag{2}$$

where V_{th} implies the thermal voltage of diode, K is Boltzmann's constant, T implies the temperature in kelvin, Q implies the elementary charge. The shunt-current is computed as,

$$I_{sh} = \frac{v \times \frac{n_p}{n_s} + I_{out} \times r_{se}}{r_{sh}} \tag{3}$$

here the number of modules attached in series and parallel as n_S and n_P. r_{se}, r_{sh} specifies series resistance, shunt resistance.

2.2. Modelling of ESS

The goal of ESS is to make the electrical grid carbon-free by storing clean energy from renewable sources [22]. ESS helps balance supply and demand, reducing greenhouse gas emissions and cutting electricity costs for users. It stores excess energy during off-peak hours and releases it when needed, primarily optimizing solar panel output, despite some energy loss during charging and discharging. Therefore, the increase in energy storage system effectiveness is computed in eqn (4).

$$ps(T) = ps(T-1) + \eta.\mu^{ess}.ee^{CH}(T) - \frac{\eta.ee^{dCH}(T)}{\mu^{ess}} \forall T \tag{4}$$

here μ^{ess} as effectiveness of energy storage system, ps as stored energy (kWh) at time T, η specifies duration of time in hours, ee^{CH} and ee^{dCH} denotes the power provided (Kw) from photovoltaic to energy storage system and ESS to load. The following limitations are used to prevent deep discharge and overcharging.

$$ee^{CH}(T) \leq ee^{CH}_{ub} \tag{5}$$

$$ee(T)^{dCH} \leq ee^{dCH}_{lb} \tag{6}$$

$$ps(T) \leq ps^{CH}_{ub} \tag{7}$$

For the purpose of creating an energy usage schedule, the EMC gets the signal of RTP, the power signal from renewable energy sources and utilities, and the consumer's appliance operating priorities.

2.3. Infrastructure for 2-way communication

Advanced Metering Infrastructure (AMI) enables bidirectional communication between electricity sources and smart meters, facilitating real-time demand response and consumer participation in DSM programs. AMI benefits power suppliers by tracking costs, identifying outages, and managing assets, while smart meters connect AMI to the Energy Management Controller (EMC) for energy usage optimization.

2.4. Modelling of appliances

Smart appliances interact with the Energy Management Controller (EMC) to optimize energy consumption. Regular appliances run continuously, while Shiftable Uninterruptible (SUAs) and Shiftable Interruptible (SIAs) appliances collaborate with the EMC to reduce peak demand, lower costs, and minimize emissions. Examples of SIAs include dishwashers, water heaters, and humidifiers, while SUAs include electric cars, washing machines, and dryers [23,24]. The overall energy usage per day for SIAs can be calculated as follows:

$$e^{SHI} = \sum \gamma_{SHI} \in d_{SHI} \left(\sum_{T=1}^{24} \Omega_{SHI} \times \gamma_{SHI}(T) \right) \tag{8}$$

here d_{SHI}, Ω_{SHI}, and γ_{SHI} implies every SIA, power, and on/off status appliances; e^{SHI} implies net consumption of energy, and β implies unit price.

The net cost per day of every Shiftable Interruptible Appliances at time T is computed as follows

$$\delta_A \xi_{SHI} = \sum \gamma_{SHI} \in d_{SHI} \left(\sum_{T=1}^{24} \Omega_{SHI} \times \beta(T) \times \gamma_{SHI}(T) \right) \tag{9}$$

The net energy-consumption per day for Shiftable Uninterruptible Appliances are computed as follows,

$$e^{SHU} = \sum \gamma_{SHU} \in d_{SHU} \left(\sum_{T=1}^{24} \Omega_{SHU} \times \gamma_{SHU}(T) \right) \tag{10}$$

here A_s as sum of Shiftable Uninterruptible Appliances, e^{SHU} represents net energy consumption, $d_{SHU} \in A_s$ as each appliance from SIAs, Ω_{SHU} as power-consumption of all appliances, γ_{SHU} as status of the appliances' on/off. The total daily cost of all Shiftable Uninterruptible Appliances in time T may be calculated as follows.

$$\delta_A \xi_{SHU} = \sum \gamma_{SHU} \in d_{SHU} \left(\sum_{T=1}^{24} \Omega_{SHU} \times \beta(T) \times \gamma_{SHU}(T) \right) \tag{11}$$

2.5. Problem formulation

The main goals of the proposed methodology are to reduce electricity costs by coordinating consumer power use patterns, reduce carbon emissions, improve user-comfort, reduce PAR, and deal with the demand-supply imbalance. Initially, each aim is enlarged and articulated separately. This leads to the formulation of the whole demand side management issue. The cost of energy is the amount charged by a utility provider to a client for the consumption of power within the specified period. The proposed method contains 2 kinds of appliances: SUAs and SIAs. The entire cost is calculated mathematically as follows:

$$\prod = \delta_A \xi_{SHI} + \delta_A \xi_{SHU} \tag{12}$$

where, Shiftable Interruptible and Uninterruptible Appliances of Net Electricity Costs are expressed as $\prod$ by consumers.

Carbon emissions, a consequence of operating Shiftable Interruptible and Uninterruptible Appliances, can be quantified through equation (13).

$$y = \frac{AVGep}{\in \times \varsigma \times \zeta} \tag{13}$$

The carbon emission in pounds is shown in equation (13), wherever $AVGep$ as average electricity price, $\in$ as cost per kWh, ς as electrical emission factor, ζ as number of hours within a day.

PAR is the peak to average power demand for particular time-slots. The PAR decrease benefits utilities and consumers alike because it assists to close the gap amid the supply and demand. It is denoted by PAR and it is mathematically expressed below:

$$PAR = \frac{MAX_{T \in t}(\Phi_t)}{\frac{1}{t} \sum_{T=1}^{t} \Phi_t} \tag{14}$$

here the energy consumed by the appliance of Φ_t at time T.

User comfort in smart homes depends on factors like energy usage, waiting time, air quality, temperature, humidity, illumination, and user demographics. The study assesses user satisfaction using the delay-time-rate (DTR), measuring appliance startup delays. When the Energy Management Controller (EMC) incentivizes load shifting, users may face delays, with lower DTR resulting in higher utility costs and vice versa. It is a trade-off between the cost of power and the DTR. Thus, the user comfort based on delay-time-rate is expressed in equation (15).

$$\omega_B = \frac{\sum_{T=1}^{t}\sum_{B=1}^{N}\left(t_{B,T}^{0,UNSCH} - t_{B,T}^{0,SCH}\right)}{t_B^{LO}} \tag{15}$$

The ω_B communicates an appliance-specific delay time rate based on operational delays or advancements, $t_{B,T}^{0,UNSCH}$, $t_{B,T}^{0,UNSCH}$ represents the status of appliance without and with scheduling, t_B^{LO} is the length of net operation time-slots [25,26]. Depend on real time pricing signal and consumer priority, the heuristic-based EMC schedules consumer power utilization. An appliance can experience maximum delay and it is specified in equation (16).

$$\omega_B^D = t_B^T - t_B^{Lo} \tag{16}$$

where An appliance may experience a maximal delay of ω_B^D while switching from operating during peak to off-peak hours, t_B^T as appliance of net time-interval. The greatest delay has a negative relationship with user comfort, i.e., as ω_B^D increases, so does the user comfort. Equation (17) can be used to calculate the percentage of discomfort.

$$d = \frac{\omega_B}{\omega_B^D} \times 100 \tag{17}$$

By scheduling user energy usage, the DSM problem aims to lower electricity prices, carbon emissions, user irritability, and PAR. The objective-function is signified as the problem of minimization in below equation.

$$MIN\left(\prod + y\right) \tag{18}$$

The minimization issue in equation (18) consists of below restrictions:

$$PAR = \frac{MAX_{T\in t}(\Phi_T)}{\frac{1}{t}\sum_{T=1}^{t}\Phi_T} \le p_C \tag{19}$$

$$t_{MIN} \le T \le t_{MAX} \tag{20}$$

$$\sum_{T=1}^{t}\Lambda_T^{UNSH} = \sum_{T=1}^{t}\Lambda_T^{SH} \tag{21}$$

$$z_T^{UNSCH} < = z_T^{SCH} \tag{22}$$

$$i_T^{UNSCH} = i_T^{SCH} \tag{23}$$

The net PAR $\le$ grid-capacity, p_C as per restriction (19) demonstrates. Grid capacity refers to the amount of power the electrical grid can supply. This restriction aids in avoiding power shortages or blackouts. Restriction (20) defines the scheduling interval. Restriction (21) enforces a power consumption limit to keep overall power usage consistent before and after scheduling [27,28]. Restriction (22) ensures that the appliance's status changes between before and after scheduling. Similar to the previous example, equation (23) displays that the operating times of the appliances before and after scheduling are equal, from which, T_1 to T_{24} as time-slots, i as operating time of appliances.

3. Energy management using proposed EMAO approach

The manuscript proposes an EMAO method for SG energy management, aiming to reduce costs and peak power usage. It includes load classification, automatic demand response shedding, and creates an optimal power schedule based on price, renewable energy sources, consumer priority, and appliance ratings. The system employs a two-way communication infrastructure, and the method combines the Mexican Axolotl Optimization (MAO) and Honey Badger Algorithm methods. Thus the stepwise process of the proposed method is given below.

3.1. Proposed EMAO method

The Mexican Axolotl Optimization (MAO) method is a meta-heuristic process motivated by the life of axolotl's, like axolotls' birth, breeding, tissue restoration, and the manner in which they survive in the aquatic environment [29]. Axolotls have sexes; therefore there are males and females in each group. We think axolotls use their ability to change color to protect them and evade predators. The TIRA acronym stands for Transition from the state of Larval to Adult, Reproduction, and Assortment, as well as Injury and Restoration. These four iterative processes make up the MAO technique. The HBA is a meta-heuristic optimization technique that draws motivation from the clever foraging strategies of honey badgers [30]. The HB's dynamic search behaviour with digging and honey seeking procedures are essential to the HBA exploration and exploitation phases. To find food, honey badgers dig or follow the scent of the honeydew bird. The HBA strategy is used in this research to improve the updating behavior of the MAO method. The energy management problem is handled by utilizing this approach. The proposed method's stepwise procedure is explained below.

Step 1. Initialization

Initiate the input-parameters, like real-time pricing signal, power of sources, stopping criterion.

Step 2. Random Generation

The population is created randomly.

$$F_i = \begin{bmatrix} (S)^{11} & (S)^{12} & \cdots & (S)^{1n} \\ (S)^{21} & (S)^{22} & \cdots & (S)^{2n} \\ \vdots & \vdots & \vdots & \vdots \\ (S)^{m1} & (S)^{m2} & \cdots & (S)^{mn} \end{bmatrix} \tag{24}$$

Step 3. Calculation of Fitness

The fitness is calculated depending on the objective function. Thus, it is computed below,

$$Fit_{OBJ} = Obj\left(M_j, F_j\right) = Min(Cost, PAR) \tag{25}$$

Step 4. Categorise of male and female populations

Two subgroups are created once the individuals are divided into female and male groups based on the axolotls, which emerge owing to their sex.

Step 5. Conversion from larvae to adult state

As axolotls mature from larvae to adults, males undergo physical changes to attract compatible mates. The best female and male axolotls for breeding can be selected depending on the objective function that considers the inverse-probability transition for each sex.

$$p(M,F)_j = \frac{Obj\left(M_j, F_j\right)}{\sum Obj\left(M_j, F_j\right)} \tag{26}$$

Step 6. Updating the position of agents

To update the position, the phases of honey and digging are used.

Step 6.1. Digging phase

It is computed as,

$$X_{NEW} = X_{PREY} + F \times \alpha \times i \times X_{PREY} + F \times R_3 \times \beta \times D_I \times [\cos(2\pi R_4) \times (1 - \cos(2\pi R_5))] \tag{27}$$

$$F = \begin{cases} 1 \rightleftarrows\rightleftarrows\rightleftarrows\rightleftarrows\rightleftarrows, if \rightleftarrows R_6 \leq 0.5 \\ -1, \rightleftarrows Else \end{cases} \rightleftarrows \tag{28}$$

Step 6.2. Honey phase

It is computed as,

$$X_{NEW} = X_{PREY} + F \times R_7 \times \beta \times D_I \tag{29}$$

Step 7. Phases of Exploitation and Exploration

The exploitation and exploration is calculated as

$$Explor \rightleftarrows \% = \frac{div'}{Max \rightleftarrows (Div)} \times 100 \tag{30}$$

$$Exploit \rightleftarrows \% = \frac{|div' - Max(div')|}{Max \rightleftarrows (Div)} \times 100 \tag{31}$$

Step 8. Stopping criterion

Verify the stopping criterion, if it satisfies the condition means the optimum result is attained, else continue the procedure. Flowchart of EMAO is depicts in Fig. 2.

4. Results and discussion

Here, the simulation outcomes for the performance of the proposed technique are analyzed. The major proposed EMAO method minimizes the cost based on the automatic load shedding and classification of load. The proposed system is simulated in MATLAB software and it is compared with different existing PSO, HGPO, and GA methods. The proposed method is executed based on three scenarios like PAR determination without PV-battery systems, scheduling the home appliances with PV, Photovoltaic battery systems-based scheduling.

Cost analysis of real time price is shown in Fig. 3. At 1–7 h, the cost of demand response is varied from 9 to 13 cents/kWh and then the cost is increased up to 27.5 Cents/kWh at 8–10 h. After that, cost is reduced below 10 cents/kWh at15 to 24 h. Estimation of Solar Irradiance is shown in Fig. 4. Here, the solar irradiance varies with time. At the time of 1–6h, solar irradiance remains 0. From the time of 6h, it gradually rises and reaches to the peak in noon time. And it remains constant at 1200(W/m^2) from hour 11 to 15. Again at the time of 15h, solar irradiance gradually decreased from 15h to 20h. At the time of 20h–24h, it remains constant in 0.

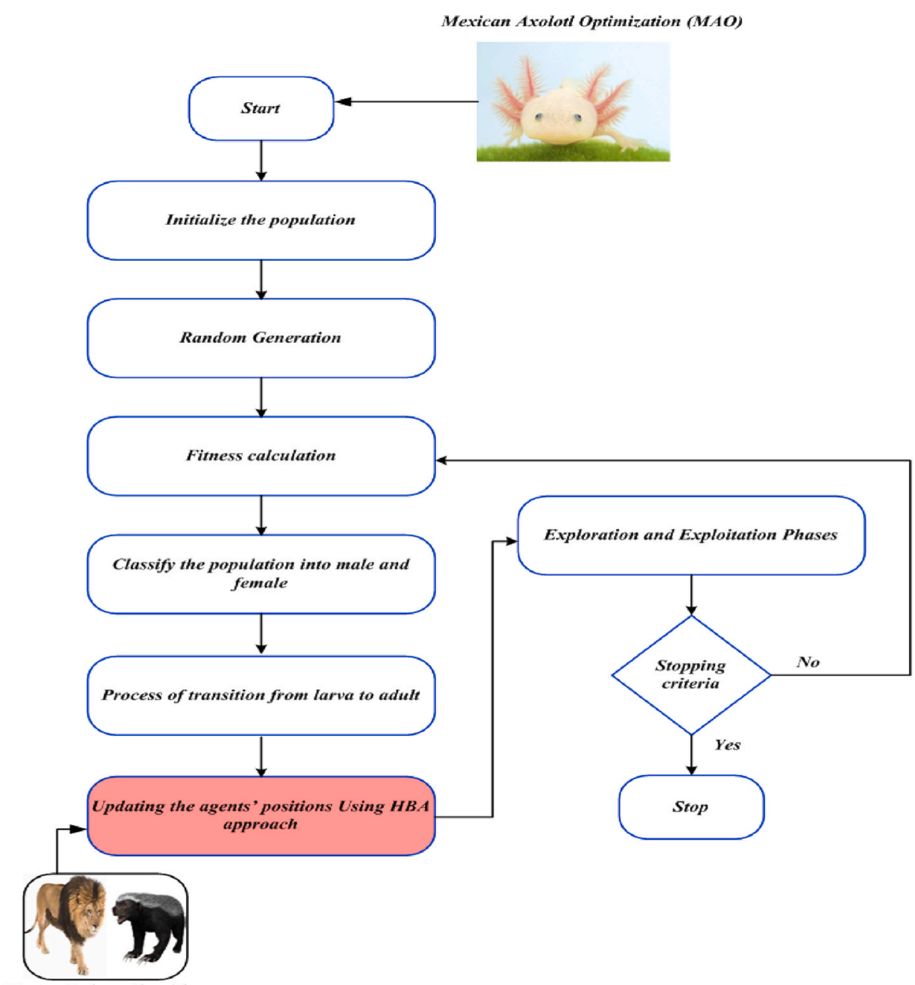

Fig. 2. Flowchart of EMAO

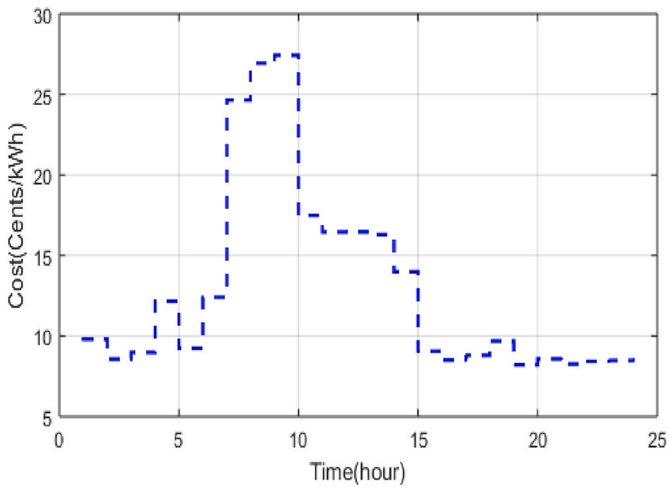

Fig. 3. Cost analysis of real time price.

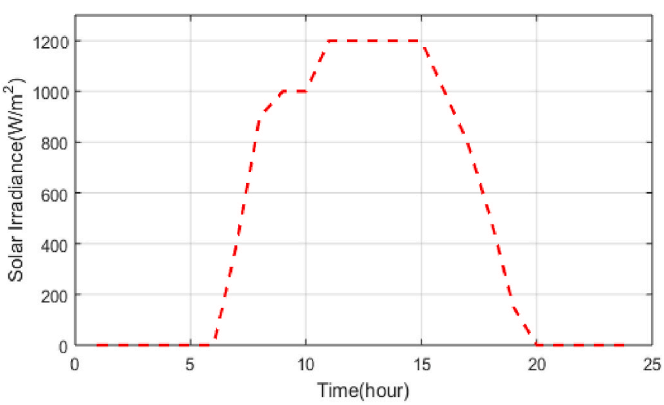

Fig. 4. Estimation of Solar Irradiance depends on time.

In Fig. 5, the graph tells about how the temperature rises an hour to hour based on time. Here, the temperature is represented as degree Celsius and time an hour. The changes happen from 1h to 24h. At the time of 1hr, the temperature starts to rise gradually and reaches to the peak of 30 °C at 13h. And again, it decreased from the time of 13h to till 24h. In Fig. 6, this graphical representation shows the level of energy stored in battery based on time. At 7h, the storage level rises step by step till 18h. Then, it remains constant till 24h between 250Ah and 300Ah. In Fig. 7, this graphical representation shows the three factors of RSE. They

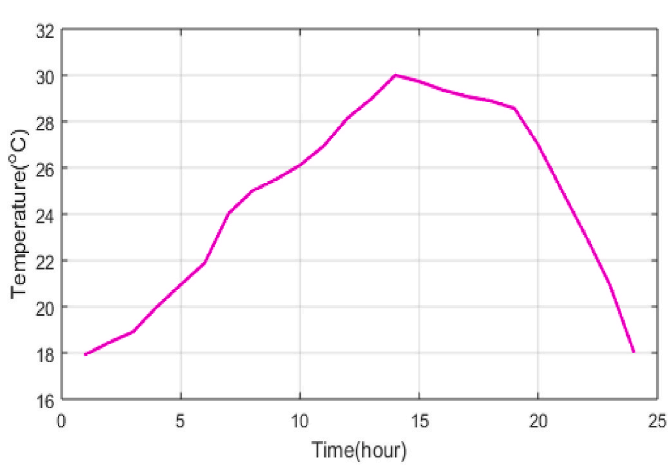

Fig. 5. Ambient temperature depends on Time.

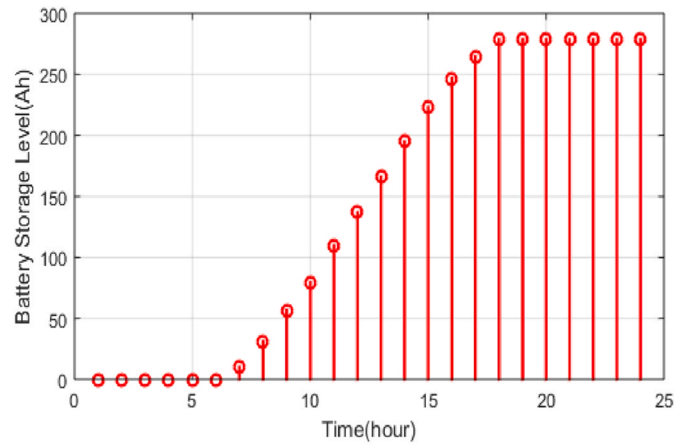

Fig. 6. Analysis of Battery storage level.

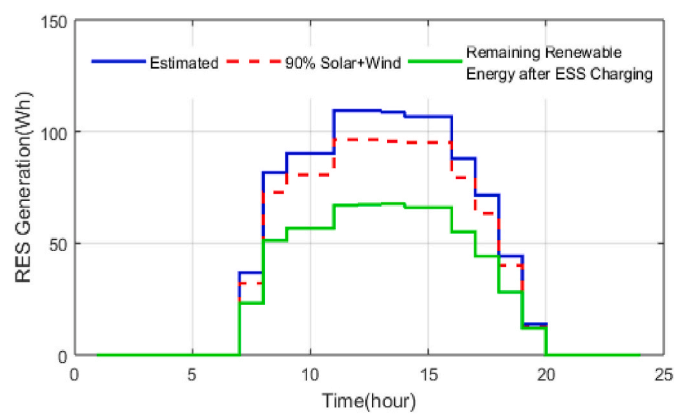

Fig. 7. Evaluation of generated rse..

are: 1) Estimated renewable energy generation, 2) Percentage of Solar and Wind power generation, 3) Remaining RE after ESS Charging. These factors are evaluated based on the time. These three estimations remain 0 till 7h, then they increases step by step till 11h. After that, till 16h they remain constant at certain value. Then, they gradually decrease up to 24h.

Case 1. Investigation Performance of Proposed Method based on without PV-battery systems

In this case, the performance of the proposed approach is executed without PV-battery systems. Fig. 8 depicts the Analysis of Electricity Cost. In Fig. 8, the graphical representation shows the analysis of electricity costs based on the proposed method. The cost of electricity is compared between GA, PSO, proposed, and HGP. The electricity cost of the proposed is lesser than the GA, PSO, and HGP methods. Hence, the proposed method gives a better result than existing methods. This analysis is made without a PV battery system. In Fig. 9, the analysis of electricity costs based on GA, PSO, HGPO, and the proposed methods are 690 cents, 590 cents, 550 cents, and 400 cents, as shown in the figure. This estimation is based on without PV battery system. The electricity cost of the proposed technique is better than the GA, PSO, and HGPO methods during off-peak and mid-peak hours.

Fig. 10 shows the graphical representation of Peak to Average Ratio based on GA, PSO, HGPO and proposed method per time slots. GA, PSO, HGPO and proposed method are evaluated as PAR by 2.9, 3.49, 3.4 and 2.5 respectively. Here, Proposed is better than GA, PSO and HGPO methods without PV battery system. In Fig. 11, this graphical representation show the level of CO_2 based on time. The Carbon is emission is compared with GA, PSO, HGPO and a proposed method is 3.7 pounds,

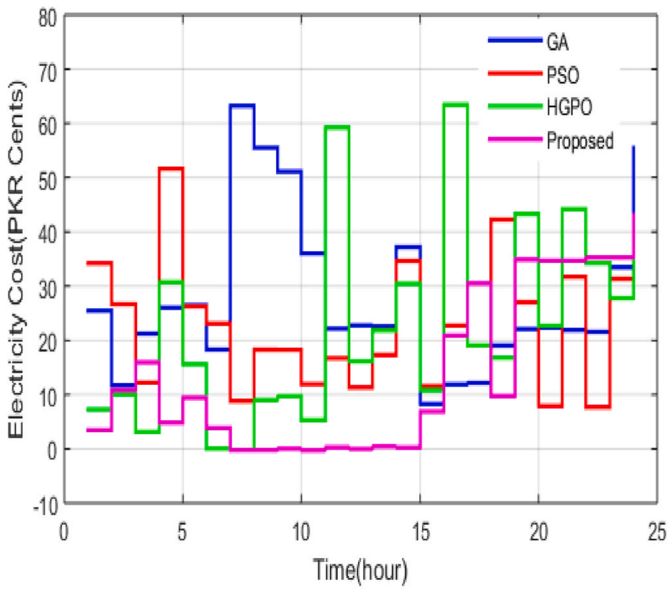

Fig. 8. Analysis of electricity cost.

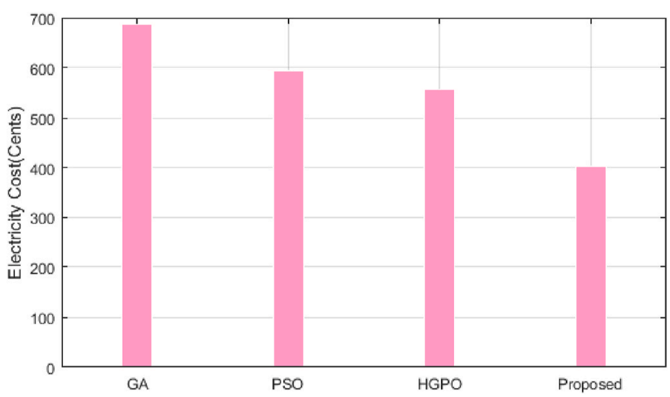

Fig. 9. Aggregated cost analysis of electricity.

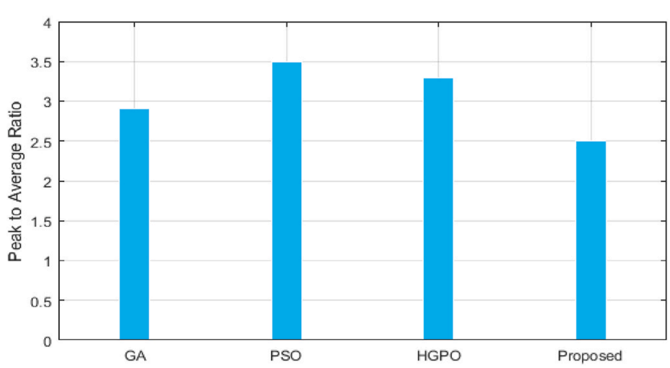

Fig. 10. Analysis of peak average ratio.

3.3 pounds, 3.2 pounds, and 2.7 pounds respectively. The proposed method effectively reduces carbon emissions for each time slot when compared to the existing approaches. This comparison is made without PV battery system.

Case 2: Investigation Performance of Proposed approach depends on scheduling the Home Appliances with PV.

In this case, the performance of the proposed technique with loaded photovoltaic-systems is examined to attain best result. In Fig. 12, the

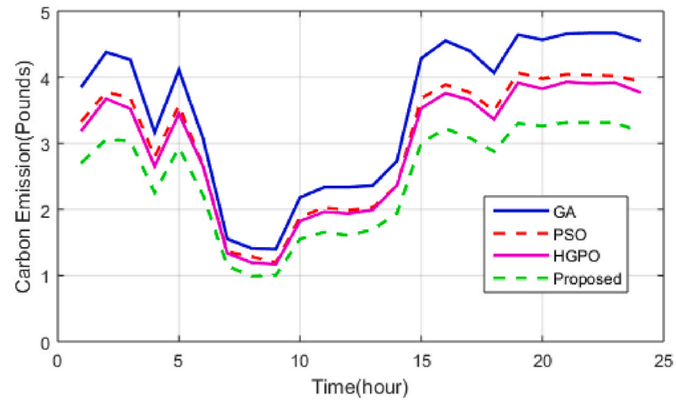

Fig. 11. Carbon Emission based on Time without PV.

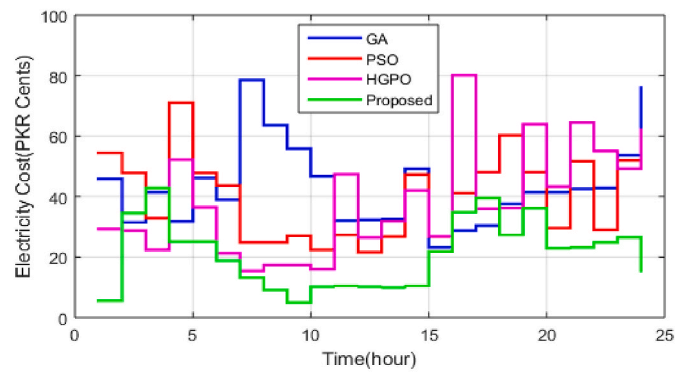

Fig. 12. Electricity cost analysis with load connected PV.

graphical representation shows the analysis of electricity cost based on proposed method. The home appliances are connected with PV system to attain best result. The maximum cost of electricity is compared with scheduled and unscheduled load between GA, PSO, and HGP and proposed. The cost of electricity of proposed is less than GA, PSO, and HGP method. This analysis made proposed method is better than existing methods without PV battery system.

Fig. 13 depicts the evaluated cost of electricity analysis with loaded PV. The electricity cost based on GA, PSO, HGPO and proposed methods are 550cents, 480cents, 450cents and 350cents. This estimation is based on with load connected PV system. The electricity cost of proposed is

Fig. 13. Evaluated cost of electricity analysis with loaded PV.

better than GA, PSO, HGPO methods under off- and mid-peak hours. Fig. 14 depicts the graphical representation of Peak to Average Ratio based on GA, PSO, HGPO and proposed method per time slots. The GA, PSO, HGPO and proposed method are evaluated as PAR by 3, 3.8, 3.3 and 2.2 respectively. The Proposed is better than GA, PSO and HGPO methods with load connected PV. Graphical representation is show in Fig. 15 that is the level of CO_2 emission based on time. Here, the carbon emission is compared between GA, PSO, HGPO and a proposed method is 3.3pounds, 2.7 pounds, 2.6 pounds, and 2.2pounds respectively. When compared to existing techniques, the proposed strategy is effective at reducing carbon emissions per each time slot. This comparison is made without PV battery system.

Case 3. Investigation Performance of Proposed approach Photovoltaic battery systems-based scheduling.

Here, the performance of proposed approach is executed with PV battery systems. Fig. 16 depicts the electricity cost analysis with PV battery system. In Fig. 16, the graphical representation shows the analysis of electricity cost based on GA, PSO, HGP and proposed method. In this, the battery system with PV is connected to attain best result. The cost of electricity of proposed is less than GA, PSO, and HGP method. This analysis made proposed method is better than existing methods with PV battery system. Fig. 17 depicts the aggregated cost of electricity analysis. This figure analysis of electricity cost based on GA, PSO, HGPO and proposed method are 520cents, 430 cents, 400cents and 310 cents. This estimation is based on PV battery system. The electricity cost of proposed is better than GA, PSO, HGPO methods during off-peak and mid-peak hours.

Fig. 18 shows Evaluation of PAR with PV battery system. Here, the values of GA, PSO, HGPO and proposed method are evaluated as 2.3, 3.6, 2.6 and 1.7 respectively. The Proposed gives better result than GA, PSO and HGPO methods with PV battery system. In Fig. 19, the graphical representation shows the level of CO_2 emission based on time slots. Here, the level of Carbon emission is compared between GA, PSO, HGPO and a proposed method. This method has an evaluation of 3.3pounds, 2.49pounds, 2.3pounds, and 1.8pounds are compared. The proposed method is efficient in reducing the carbon emission per each time slots, when compared with existing methods. This comparison is made with PV battery system. In Fig. 20, the graph tells about how the consumers faced delay in power usage, while using appliances. The projected average delays for humidifiers, water heaters, dishwashers, EVs, washing machines, and textile dryers for GA-based scheduling are 1.3, 1.55, 0.7, 1.8, 1.3, and 1 h, respectively. The PSO faces average delays of 1.4, 1.2, 1, 0.6, 1.8 and 1 h respectively on such appliances. In HGPO method, average delays of 0.7, 1.3, 1.28, 1.8 and 1.35h respectively on such appliances are shown in graph. This proves that the proposed technique performs better than the existing approaches.

Table 1 compares the investigation performance of different algorithms for the proposed method without PV-battery systems in Case 1. The proposed method has the lowest cost of 400 cents, the lowest carbon emissions of 2.7 pounds, and a moderate performance-to-cost ratio

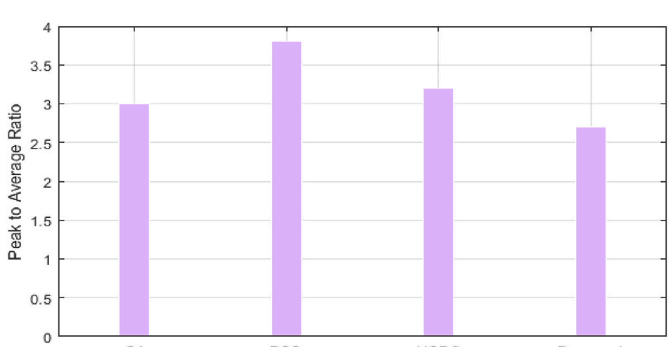

Fig. 14. Estimation of PAR with loaded PV.

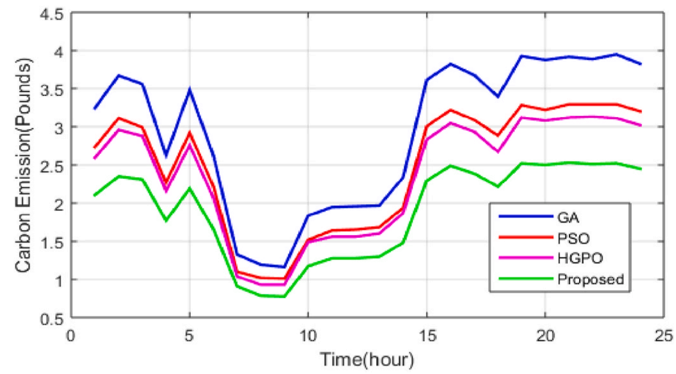

Fig. 15. Analysis of Carbon emission with loaded PV.

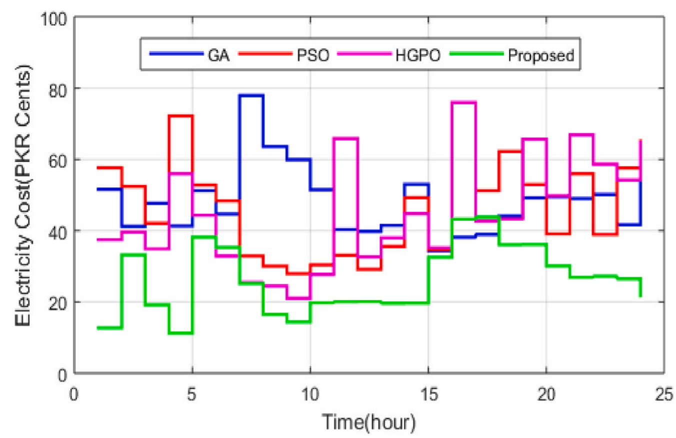

Fig. 16. Electricity cost analysis with PV battery system.

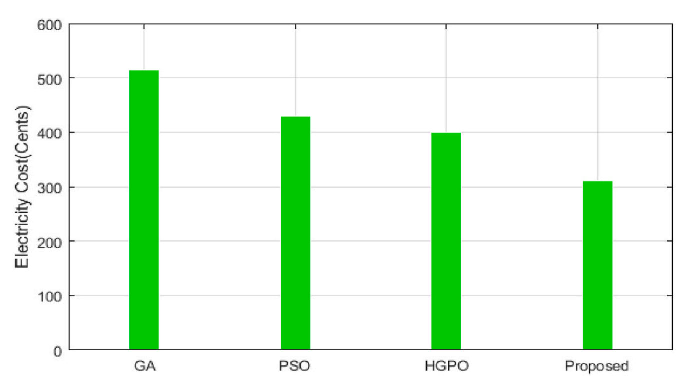

Fig. 17. Aggregated cost of electricity analysis.

(PAR) of 2.5. This suggests that the proposed approach is the most cost-effective and environmentally friendly option among the algorithms considered in Case 1. Table 2 compares the Investigation Performance of Proposed Method schedules the Home Appliances with PV in case 2. The proposed method has the lowest cost of 350 cents, the lowest carbon emissions of 2.2 pounds, and a moderate performance-to-cost ratio (PAR) of 2.2. This implies that the proposed method is highly cost-effective and ecologically friendly alternative among the algorithms studied in Case 2. Table 3 compares the Investigation Performance of Proposed Method with Photovoltaic battery systems-based scheduling in case 3. The proposed approach performs better than other algorithms with the lowest cost of 310 cents, the lowest carbon emissions of 1.8 pounds, and a PAR of 1.7. This suggests that the proposed technique is the most cost-effective and environmentally friendly option among the

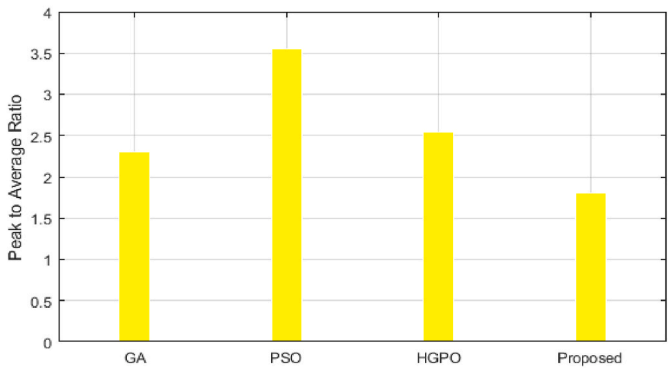

Fig. 18. Evaluation of PAR with PV battery system.

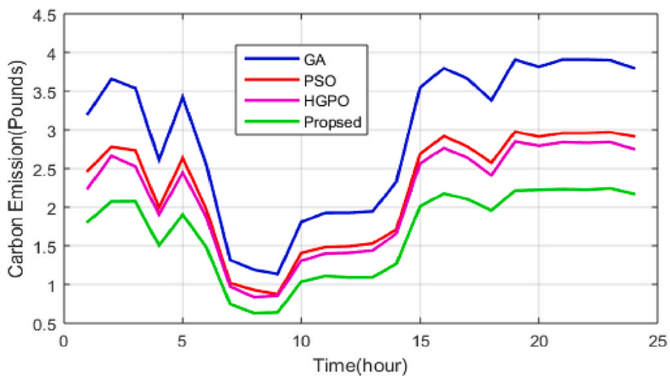

Fig. 19. Analysis of Carbon emission based on hour.

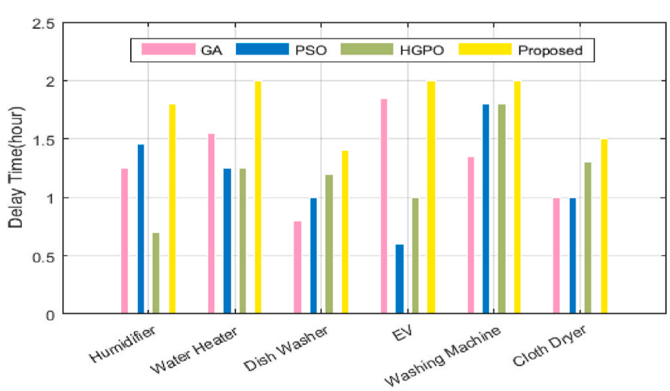

Fig. 20. Analysis of Delay time in PV battery system.

Table 1
Study Performance of Proposed Method without PV-battery systems in case 1.

Techniques	Cost (Cents)	Peak to average ratio	Carbon Emissions (Pounds)
GA	690	2.9	3.7
PSO	590	3.49	3.3
HGPO	550	3.4	3.2
proposed	400	2.5	2.7

algorithms considered in case 3.

5. Conclusion

- The manuscript proposes an enhanced EMAO method for reducing the cost of the SG system through automatic demand response shedding with load classification, considering photovoltaic and battery as the system's source.
- The proposed method effectively solves demand side problems and optimally schedules the system. It leads to lower power consumption costs, reduced peak-valley and peak-load, decreased carbon emissions, and prevents rebound peaks without causing significant inconvenience to consumers. The method also reduces the PAR value of the system.
- The evaluation outcome provides that the proposed technique provides better than the GA, PSO, and HGPO methods when applied with a PV battery system. It achieves better results in terms of cost reduction, carbon emissions, and minimizing delays in power usage for various appliances.
- The outcome shows that the EMAO method consistently achieves the lowest cost, with values of 400 cents in Case 1, 350cents in Case 2, and 310 cents in Case 3. Additionally, the EMAO algorithm consistently produces the lowest carbon emissions, with values of 2.7 pounds in Case 1, 2.2pounds in Case 2, and 1.8 pounds in Case 3. Furthermore, the algorithm maintains a moderate performance-to-cost ratio, with values of 2.5 in Case 1, 2.2in Case 2, and 1.7 in Case 3, indicating its cost-effectiveness and efficiency.
- In summary, the proposed enhanced EMAO method offers a solution for cost reduction and demand management in the SG system. It provides advantages in terms of cost efficiency, carbon emissions reduction, and minimizing delays. The manuscript contributes to the form of information by presenting a more effective and efficient approach compared to existing methods.
- The limitations of this study include the assumption of fixed consumer behavior and the focus on a specific combination of algorithms. Future work could explore dynamic consumer behavior and investigate the applicability of other hybrid algorithms in the energy management framework. Additionally, the integration of other RESs and the consideration of different consumer segments could further enhance the efficiency and of the proposed method.
- The study shows that it have important implications for the practical implementation of demand-response approaches and the optimization of SG systems, ultimately leading to cost savings, reduced carbon emissions, and improved energy management.

Table 2
Investigation Performance of Proposed Method schedules the Home Appliances with PV in case 2.

Techniques	Cost (Cents)	Peak to average ratio	Carbon Emissions (Pounds)
GA	550	3	3.3
PSO	480	3.8	2.7
HGPO	450	3.3	2.6
proposed	350	2.2	2.2

Table 3
Investigation Performance of Proposed Method with Photovoltaic battery systems-based scheduling in case 3.

Algorithms	Cost (Cents)	Peak to average ratio	Carbon Emission (Pounds)
GA	520	2.3	3.3
PSO	430	3.6	2.49
HGPO	400	2.6	2.3
proposed	310	1.7	1.8

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CRediT authorship contribution statement

Revathi R: Methodology. **Senthilnathan N:** Supervision. **Kumar Chinnaiyan V:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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