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Hybrid Bio-Inspired Optimization Algorithms For Sustainable Energy Management System of Smart Grid

Abstract: - Due to climate change and the energy resource crisis, the power generation sector is shifting toward renewable energy sources (RESs) over conventional fossil fuels. The present situation demands the best possible inclusion of RESs in the system for the new purpose. This study suggests the combination of two bio-inspired algorithms, Deer Hunting Optimization (DHO) and Lion's Algorithm Optimization (LAO) for effective Energy Management System (EMS) in hybrid renewable energy systems(HRES), along with the optimal use of RESs and energy storage systems (ESS). The recommended research optimizes power and distribution networks through continuous IoT data monitoring, necessitating demand response(DR) development for EMS distribution networks. The analysis and observation of many objectives, such as optimization of end-user satisfaction (the reductions in waiting time), Peak to Average Power Ratio (APR), Hourly Demand (HD), and Total Energy Cost, are conducted. The DHO and LAO combined algorithm has been developed specifically to accomplish these goals. Consequently, this innovative approach can reduce total electricity costs, alleviate consumer dissatisfaction, streamline computational processes, and ensure the stability of hourly power consumption.

Keywords: Energy management system, Energy optimization, Hybrid renewable energy systems, Bio-inspired algorithms, Lion algorithm, Deer Hunting Optimization, and Smart grid.

I. INTRODUCTION

In the present scenario, researchers and engineers are showing concern about the rapidly rising global energy crisis and the environmental impact of non-renewable energy sources, as well as the required reliability and security of the system. Thus the power industry is moving from a conventional power generation grid to RESs integrated smart grid. Generally, solar PV and wind generation are the most commonly used major RESs incorporated with energy storage systems in smart grid systems [1]. An optimal smart city or smart grid system must be economical, reliable, and environmentally friendly [2]. Through a new collaborative framework that facilitates IoT, grid infrastructures can interrelate multiple technologies, methods, structural constraints, operating necessitates, and communication solutions [3]. IoT may enable global computing to detect and control various scales of energy demand areas. These data are collected by using multiple wireless sensors at various points of the system. Overall integrated energy system consumer apparatus provides numerous data types to EMS, resulting in interconnections issues and overall electricity sustainability. Demand side management majorly works on two functions: load management as per hierarchy level and demand response. Sensors and smart meters are deployed in Every demand sector. Smart meters are used to communicate cost signals and to regulate power consumption. smart meters are generally capable of bidirectional communication and unidirectional electricity flow. According to the peak hour tariff, all types of equipment are scheduled with defined time slots by the energy management company [3, 4]. To design an optimal RES-integrated smart grid, which requires appropriate techniques and methods for efficiently utilizing energy in order to maintain the production supply chain. The modern energy demand of a smart city cannot be satisfied by conventional grids, therefore smart grids (SG) have been introduced. The SG enhances the reliability and robustness of the proposed system and it depends on the commercial, industrial, and household areas [4, 5].

Integrating EMS aims to interconnect each and every component of the system to share an information model, which will be helpful for efficient energy management. Researchers and scientists have already developed numerous Demand Response (DR) methods in the last few years, to lower Average Power Ratio (APR), imported energy, and costs of electricity. Numerous researchers have analyzed the benefits of DR systems in residential areas. We performed a wide variety of simulations to show that our suggested sophisticated algorithm reduced APR,

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electricity prices, and demand side awaiting duration. This is done by designing a smart network for industry demand response and demand side management considering different Length of Operational time (LOTs) and device power ratings.

II. BACKGROUND OF RESEARCH WORK

Several researchers have effectively reduced peak demand and expenditures by solving a system development problem with three meta-heuristics algorithms, the author has effectively reduced peak demand and expenditures by solving a system development problem with three meta-heuristics algorithms[5-10]. In their article [11], the researcher introduced a game theory-based approach to minimize the overall energy cost and the APR. However, consumer satisfaction was not considered a constraint in this study. Other researchers have used heuristic algorithms and PSO algorithms for smart home planning. The author of article [12] describes an innovative technique to minimize the overall energy expenditure and to design an efficient EMS for RES-integrated SG. However, the initial installation expenditures of RES have been overlooked here. In this paper[13], the researcher has introduced another BESS-based model with significant customer satisfaction. In this model, they prefer to charge the home appliances when the tariff is low.

In [14] writers employed three meta-heuristic methods like harmony search algorithm(HAS), Enhanced differential evolution(EDE), and bacterial foraging algorithm(BFA), ensuring optimum usage of the power supplies. HSA has the BETTER performance to minimize cost compared to BFA and EDE. Devices were scheduled as per the day-ahead pricing (DAP) alert.

In this paper[15], the author has proposed another EMS with cost-associated DR for IoT-enabled residential campuses. This Wind Driven Bacterial Foraging algorithm (WBFA) is a combination of WDO and BFO algorithms. Authors have described an EMS in challenging circumstances to reduce microgrid(MG) operation expenditure by implementing modified particle MPSO Optimization problems with real-time data.

Similarly, some authors compare GA and the CSA for overall cost computation, waiting duration, and APR reduction. GA cuts the cost by 22.90%, while CSA cuts it by 22.81%. 21.56%. GA reduced APR by 18.37% to 3.63. GA is better for CSA (19.0% decrease) and cost reduction and APR decrease with CSA[16-18]. In this article[19], the author employed a Q-learning method for optimal Demand response in a completely automated household setup. DMS uses the BPOS energy model to reduce housing energy expenditures by scheduling equipment, but consumer dissatisfaction caused by scheduling is neglected [21]. In [20] the researchers improved reliability and SG efficiency to reduce overall energy costs by optimal designing of data centers and cloud grids. In [22] the researchers developed a demand response system to reduce costs and maximize security. The authors have introduced a stochastic probabilistic optimum energy management (OEM) of renewable-based microgrids integrating unpredictability. OEM of MG optimizes distributed power generation, demand response, and cost of electricity. A mixed bio-inspired method created on a k-point estimation technique using swarm intelligence solves optimization functions worldwide in both deterministic as well as probabilistic ways. To achieve the optimal energy management of the Microgrid, the issue is designed in three scenarios to test the hybrid PEM-MOGSO method's resilience in manipulating optimal operation plans and analytical cost estimations [23]. A hybrid bacterial foraging optimization algorithm-particle swarm optimization (hBFOA-PSO) optimization method is used in this paper to analyze the dynamic voltage/reactive power efficiency of a freestanding wind-diesel energy system. With the objective of increasing the voltage stability of the system and effectively suppressing voltage/reactive power oscillations during system-wide occurrences like changes in electrical demand and the speed of the wind, the hBFOA-PSO method is employed to optimize the gains of the PI controllers of the AVR and STATCOM [24]. In this study, the authors developed a home energy management system (HEMS) to transfer electrical load in a single home with numerous devices a day ahead and in real-time. Three heuristic algorithms—BFA, ACO, and a hybrid HB-ACO—are used to schedule household devices. Electricity cost, APR, and comfort for consumers in terms of waiting time are taken into account to assess effectiveness[25]. This work develops IGSS-DHOA, an intelligent grid scheduling method that uses the deer hunting optimization algorithm (DHOA) and schedules in a way that minimizes the grid platform's makespan. The IGSS-DHOA method is primarily based on people's propensity for executing deer. With the candidate solution (schedule) as the input, it also generates an objective purpose, and the makespan value, which indicates the candidate solution's effectiveness, is the result. Simulation findings demonstrated that the IGSS-DHOA technique outperformed modern state-of-the-art methods with the lowest average costs for processing [26].

Researchers have developed many bio-inspired algorithms. Most of them have ignored consumer discomfort because of equipment scheduling end-user electricity and APR. Thus, in this study, we apply a combination of two bio-inspired algorithms for energy management to mend the in-demand sector. as they impact Smart Grid reliability, stability, sustainability, and security. Proposed deer hunting optimization (DHO) and Lion Algorithm optimization (LAO) are implemented in this section. Formulating the objective function improves performance. This paper aims to lower energy costs by making buying easier. IoT cloud catastrophe management connects smart residences. Like DR signals, this IoT cloud optimizes load and programming.

Objective and contribution

- First, we look at the EMS study using Internet of Things (IoT) technology based on hybrid distribution systems. This has been done through innovation to obtain a general optimal solution with the help of search agents.
- The optimization issues are addressed in this EMS study and by the application of the Deer Hunting Optimization (DHO) algorithm and the Lion Algorithm Optimization (LAO). The primary goal is to optimally control power and distribution system resources by constantly monitoring the power data, as the communication framework depends on the IoT, which can reduce end-consumer irritation due to equipment scheduling in the household, commercial, or industrial domains to reduce energy costs and APR.
- The suggested system is performed on the MATLAB/Simulink working platform, and its performance is evaluated using existing particle swarm optimization (PSO), genetic algorithm (GA), crow search optimization (CSO), and deer hunting optimization (DHO) techniques.
- The objective of the proposed LAO is to optimize customer satisfaction via efficient scheduling of demand components; such as getting very low the cumulative electricity cost of consumers as well as the APR.

Here is a list of the articles identified.: Section III describes the system modeling. Section IV delivers the proposed methodology of the hybrid bio-inspired optimization. The analysis of the computation results for smart grid energy management and the outcomes of the combined method are laid out in Section V, and finally, Section VI discusses the conclusion of the proposed technique and its potential future scope.

III. SYSTEM MODELLING

A. EMS of Distribution System Integrating The Internet of Things

It is well known that there is a need for a more efficient and effective approach to producing and consuming electrical energy. Energy management, also known as adjusting energy generation and utilization, may significantly impact the path electric energy takes from generation to utilization. EMS of power supply systems takes into account RES and ESS as well as several regular energy sources. The balance between generation and demand is achieved through the use of diverse data, such as weather forecasts and energy market data, during improved communication and control infrastructure[27]. The researchers are involved in the field of energy management since it results in the regulation of the generating time and demand for various units, which lowers generation costs, by directly controlling and monitoring the energy resources as well as controllable loads. EMS at distribution systems plays a significant role in system operation and control and makes the power system function more capable of monitoring, controlling, and saving energy.

B. Integration Of Iot In Power Generation From RESB

A modern, reliable, and structured energy system helps smart cities function effectively. IoT can help smart cities meet their power requirements by generating electricity from RES. Remotely observing and regulating machinery infrastructure with such technologies improves businesses[28]. The following are some aspects of adopting IoT with RES-integrated SG:

- **Automation:** Sophisticated IoT solutions enable automated interventions for operational efficiency. Adjusting devices boost operational efficiency. The key benefit of IoT technology is real-time data that minimizes wastage[29]
- **Economical Benefits:** Electricity distribution operators could analyze power demand statistics using IoT analytics to optimize market dynamics. Integrating IoT in microgrids and smart grids offers significant economic benefits by enabling more efficient energy management and reducing operational costs. IoT devices facilitate real-time monitoring and data analytics, optimizing energy usage and reducing wastage (Olatunde et al.,2024)[30]. This improved efficiency can lower utility companies' consumer energy bills and operational expenses. Additionally,

predictive maintenance enabled by IoT can prevent costly equipment failures and extend the lifespan of grid infrastructure. Electricity distribution operators could analyze power demand statistics using IoT analytics to optimize market dynamics (Vritti et al.,2024)[31].

- **Overall Grid Management:** The IoT improves grid management. The IoT provides precise information that helps power providers to monitor all parameters such as voltage, alter demand, and design an efficient power system. Real-time grid sensors can alert controllers about disruptions. Datasets let employees turn off hazardous networks to avoid electric flames, as well as other risks. Smart switching technology can segregate the outage areas automatically. Smart switching technology can automatically segregate outage areas [32].
- **Distributed Power System:** Energy industries are moving towards the decentralized electric grid system. In parallel to managing the main power generation units, companies must integrate more grid-connected small-scale power generators. Monitoring decentralized smart grids is comparatively easier with IoT technology. Several sensors are employed in many places to monitor the SG. Providers may be able to manage the distributed power system more efficiently by receiving accurate demand data from sensors[34].
- **Residential, Commercial, and Industrial Load Segments**: Renewable energy is also being adopted by residential, commercial, and industrial load segments. IoT infrastructure will help to achieve an efficient smart city integrated with renewable energy. By adopting IoT, end-users can connect solar panels, rainfall collecting systems, smart roofs, and windows[35,36,38]. Desktop or mobile apps can control electrical equipment[37]. This analysis could help them save electricity costs and identify high power-consuming equipment.

The EMS indicated that a hybrid model might reduce electricity costs and maximize revenues. Fig. 1 shows the IoT-based EMS system layout. This research presents an IoT-based hybrid EMS distribution system. The data collection unit links to each residential, commercial, and industrial load segment through an IP address[39]. For extra administration and study, all smart home gadgets transfer energy consumption data to a centralized server through a data gathering module[40,41]. The EMS demonstrated that a hybrid system may dramatically reduce electricity costs and boost profitability. Fig. 2 shows the EMS system layout in a modified IEEE 10 bus.

C. Numerical Interpretation of the HRES System

1) Numerical Interpretation of Solar PV Framework

Photovoltaic panels turn daylight into electricity. Photovoltaic power is calculated below:

$$P_{pv} = R_t \eta_{pv} A_{pv} \qquad (1)$$

When PV panels produce power($\boldsymbol{P_{pv}}$), solar irradiation at an elevation ($\boldsymbol{R_t}$), Solar panel efficiency ($\boldsymbol{\eta_{pv}}$), and Solar's surface area ($\boldsymbol{A_{pv}}$) are all measured.

$$\eta_{pv} = \eta_{r-pv}\eta_{PC}\left[1 - N_T(T_C - T_{ref})\right] \qquad (2)$$

Where, $\boldsymbol{\eta_{pv}}$denotes the performance of the PV module, $\boldsymbol{\eta_{r-pv}\eta_{PC}}$denotes the power condition, $\boldsymbol{N_T}$ denotes the efficiency temperature coefficient of the PV module, $\boldsymbol{N_T}$ denotes PV module temperature(℃), $\boldsymbol{T_{ref}}$ is set at 25℃ [42]

$$\boldsymbol{T_C = T_A + \left[\frac{N_{OCT}-20}{800}\right] R_t} \qquad (3)$$

2) Numerical interpretation of wind turbine layout

To calculate the WT power production, use the following procedures[44,45].

$$\mathrm{P_{wind}} = \begin{cases} 0 & \text{if } \mathrm{Ws} \le \mathrm{Ws}_{CI} \\ a \times \mathrm{Ws}^3 - \beta \times P_r & \text{if } \mathrm{Ws}_{CI} \le \mathrm{Ws} \le \mathrm{Ws}_R \\ P_r & \text{if } \mathrm{Ws}_R \le \mathrm{Ws} \le \mathrm{Ws}_{CO} \\ 0 & \text{if } \mathrm{Ws} \le \mathrm{Ws}_{CO} \end{cases} \qquad (4)$$

Where w_{cis} denotes the cut-in wind speed, w_{cos} denotes the cut-off wind speed, w_{rs} rated wind speed. Rated power is presented as P_{rated}.

3) Numerical interpretation of microturbine layout

Microturbine, a small strong gas turbine, generates 20–500 kW. MT requires compressors, combustors, turbines, and generators. This article employs spilled-shaft MT[46,47].

$$C_{MT} = C_{gasMT} * \frac{P_{MT}}{\eta_{MT}} \qquad (5)$$

where C_{MT} is fuel expenditure of MT, expenditure of gas, and microgrid C_{gasMT}, generated power from MT is denoted as P_{MT}, and η_{MT} is the performance index.

4) Numerical interpretation of battery energy storage system

This battery storage system may estimate the battery's charging state based on timeframe and production calculations. When the volume of energy produced by PV panels is greater or comparable to the ratio between the energy produced in a certain period and the efficiency of the inverter, the battery is charged, and the percentage of state-of-charge is calculated using the equation follows[48]. This energy storage system calculates the charging state based on timeframe and performance. The battery is charged when PV panel energy exceeds the ratio between accurate hour's energy and inverter efficacy. The BESS charging volume is calculated by the calculation below.

$$Bt(t) = Bt(t-1) * (1-\sigma) + \left[E_g - \frac{ED}{\eta_{INV}}\right]\eta_{BC} \tag{6}$$

Where $Bt(t)$ is representing BESS charge on time, E_g is energy generated from the solar panel and wind turbines, η_{INV} is the efficiency of the inverter, η_{BC} and η_{Bdis} are the charging and discharging efficiency of BESS respectively.

$$Bt(t) = Bt(t-1) * (1-\sigma) + \left[\frac{ED}{\eta_{INV}} - E_g\right]\eta_{Bdis} \tag{7}$$

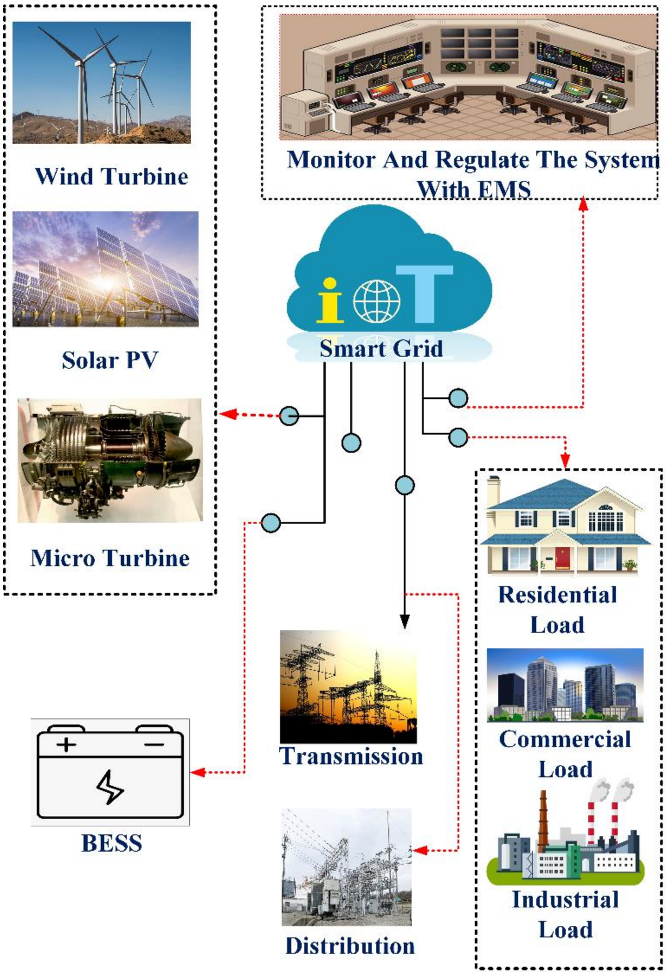

Fig 1. Proposed Grid layout

IV. THE PROPOSED METHOD OF THE HYBRID BIO-INSPIRED OPTIMIZATION

Energy Management for The Distribution System Using A Potential Hybrid Version

Particle swarm optimization, Genetic algorithm, and other optimization techniques cannot tailor solutions according to force and valve point complexity. Valve-point loading influences technique input-output. Optimization is finding superior solutions to rectify problems. Gradient-dependent algorithms require searching space derivation. They're ineffective for real problems. This encouraged modern nature-inspired optimization algorithms to compete with current optimization techniques. Deer Hunting Optimization (DHO) is a new optimization method influenced by hunters hunting deer. Hunters encircle and chase deer. That method takes wind angle, deer position, and other factors into account. After all, the leader and successor determine the aim.

This study incorporates an alternative bio-inspired algorithm for this issue. Industrial load units are used. To achieve maximum DMS performance, equipment scheduling is essential. Scheduling reduces energy costs, APR, cumulative energy consumption, device average wait duration, and consumer discomfort. In this age of energy-dependent technology, consumers prefer to accomplish their work fast rather than awaiting for their equipment to start. However, lowering consumption also reduces pricing. But sadly, most studies have overlooked the rate of disruptions and cumulative energy consumption, because these factors endanger power-system-reliability(PSR), stability, sustainability, and safety of Smart Grid

Using two different optimization methods has pros and cons. DHO autonomously shows ideal regulation parameters premised on moving toward as a whole optimal level, combining many cost functions, rapid application, etc. Local optima of individual objectives can be attached to all intention function solutions other than DHO demerits. LAO compensates the in expertise of DHO probing behavior. The DHO-LAO method avoids the weaknesses of such two different optimization algorithms individually. Thus, the hybrid IoT-based smart grid energy management method is effective.

A. Steps in the DHO-LAO Method

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

STEP 1: Initialization of samples- Hunter population Initializing starts foremost. The final output needs response, energy provided by resources, costing functions, and associated supply constraints input and randomly generates the demand side response utilizing the following expression,

$$DR = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ . & . & . & . \\ y_{n1} & y_{n2} & \cdots & y_{nn} \end{bmatrix} \tag{8}$$

where DR, represents arbitrary demand response and Y_{ij} presents random solutions.

STEP 2: Initialization with parameters- The wind direction and deer's location determine the hunters' perfect location angle matters. The wind and deer's location angle were calculated by,

$$\theta_i = 2\pi r \tag{9}$$

Here, the randomly generated value on the spectrum [0, 1] is defined as r, and the latest iteration is as i. The deer's location orientation would then be calculated using.

$\varphi_i = \theta + \pi$ where wind angle is θ.

STEP 3: Fitness Function- Every smart home component's optimal consumption is based on power costs and revenue. Assume fitness function.

STEP 4: Implementation of LAO- The implementation of the lion algorithm optimization aims to enhance customer satisfaction via efficient scheduling of demand components; such as getting very low the cumulative electricity cost of consumers as well as the APR.

STEP 5: Four primary Objectives are as follows; 1. Minimization of machine Maintenance cost; 2. Minimization of consumer energy costs; 3. Minimization of APR; 4. Adaptations of more RESs.

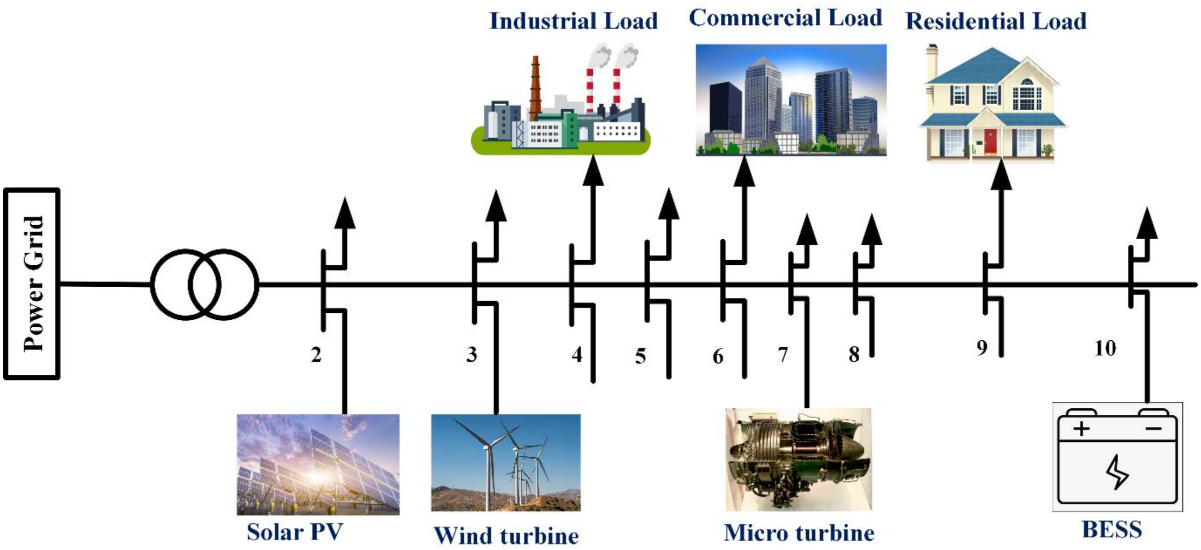

Fig 2. The modified IEEE 10-bus

B. Multi-parameter objective approach

1) Total lifespan expenditure(TLE)

The introduced technique is to estimate the expenditures of the smart grid integration system by analyzing using TLE. TLE equations are below.

$$TLE = CC + \sum_{i=1}^{N} \frac{mE+oE}{(1+d)^i} \tag{10}$$

Where CC is the capital cost, mE denotes the expenditures for maintenance, oE represents the operational expenditures, and d is the rate of inflammation.

- TLE of wind turbine: The main frame of the hybrid system utilizing WT blades is estimated to achieve the capital cost of WT that is able to be defined by the following equations. Wind turbine rotor blades revolve in the swept region, as seen from the center. Blade-swept area determines wind turbine potential production.

$$CC_{WT} = A_{WT} C_{WT} \frac{j(1+j)^n}{(1+j)^n - 1} \mathrm{b} \tag{11}$$

Operational expenditure of WT per day is- $oE_{WT} = mE_{WT} \sum_{i-1}^{240} P_{WT} T$
The maintenance expenditure of WT per year is - $mE_{WT} = A_{WT} E_{main-WT}$
Where C_{WT} is denoting the WT cost, A_{WT} is the swept area of the blade, $E_{main-WT}$ denotes the yearly maintenance expenditure of WT and j is the interest rate.

- TLE of Solar PV: Photovoltaic lifespan expenditure is measured similarly to the WT system
- TLE of microturbine: The initial capital expenditure of the microturbine is calculated thus.

$$ICE_{mt=N_{mt} C_{MAINmt} C_{HourMain\_nt} = \sum_{f=1}^{8760} C_{HourMain\_nt}} \tag{12}$$

C_{MAINmt} and $C_{HourMain\_nt}$ are the maintenance cost, and the maintenance expenditure per hour of constraint respectively.

2) Multi-parameter objective optimization constraints

By modulating ASWT, APV, NBTt, the method reduces total lifespan expenditure. The calculation following evaluates the objective function.

$$minTLE(AS_{WT}, A_{PV}, N_{BESS}, F_{mt}) = \sum_{m \in wt,pv,mt.BESS} CC_M + oE_M + mE_M \tag{13}$$

Constraints are:

$$A_{solar} A_{WT} N_{BESS} \geq 0 \tag{14}$$

$$P_{SOLAR}(t) + P_{WT}(t) + P_{BESS}(t) + P_{mt}(t) \geq P_l(t) \tag{15}$$

$$BESS_{\delta-MIN} \leq BESS_{\delta}(t) \leq BESS_{\delta-MAX} \tag{16}$$

$$BESS_{\delta-MIN} = (1 - DOD)\delta_{BESS} \tag{17}$$

overall power requirements are represented by Pi, minimum storage system charge is represented by $BESS_{\delta-MIN}$, B_{MAX} is used as the BESS's maximum charge, BESS is the BESS's nominal capacity, and DOD is the BESS's maximum depth of discharge.

DMS (Demand Side Management) and SSM (Supply Side Management) make up the smart grid's EMS (energy management system). Smart Meters (SM) use AMS (advanced metering system) technology to communicate with end users and distributors. Various devices have distinct EMC patterns. Energy Management Control (EMC) subsequently modulates its load according to the company's cost signal. Fig.1 displays the intended system layout. The cost signal is sent to EMC via Smart Meter SM. It also receives power signals from EMC and sends them to energy provider companies. Wi-Fi, ZigBee, Global System for Mobile Connectivity (GSM), and others can be used to communicate [21]. Individual segments handle various load units in an industrial system. This paper uses a crusher factory as a case study. As shown in Fig. 2, it has various AOMs with varied power ratings.

C. Lion Algorithm

One of the most aggressive animals on Earth, the lion, hunts its prey and other mammals. Lion behavior and attitude inspire Lion's Algorithm's optimum approach. The territorial lion has to protect his territory for 1–4 years since lion cubs grow up. This timeframe saw territorial or regional defense by nomadic lions. Nomadic and regional lions come to conquer that territory. If somehow the nomadic lion wins, it kills the defeated lion's every offspring and drives the mother to breed. thus the Nomadic lion becomes territorial alpha. The pride's mature cubs kill or evict the territorial lion. This intruder lion kills and has cubs with the local lioness[21, 49].

Studying their behavioral patterns as well as establishing an optimum big-scale solution inspired the method. This model computes single- and multi-variable problems. Regional protection and invasion are effective strategies. The primary solution is available first from the alpha lion, and the cubs extend that solution. When a new protection strategy (in this case, the regional lion) replaces the old one, an evolutionary process in regional defense occurs (the nomadic lion). If the recently created alternative approach is superior, the previously driving approach gets dropped[50].

The regional conquest exclusively keeps the fittest male and female lions and eliminates the rest. The Lion Algorithm stages are described below. The algorithm architecture has four main features. These are:

- Pride Creation for newer initiatives.
- Mating in order to provide a novel response;
- Regional protection;
- regional invasion to eliminate the existing solution and establish the more optimum new options.

The method is performed repeatedly until the preferred result is found. Pride is a two-solution dynamic variable-size solution. Male and female versions are available. it retains better solutions and removes poor ones. By mutation and crossing over, breeding creates new solutions. Gender gaping is the difference between resolutions, and killing young animals suggests evolved solutions are superior.

The objective function is.

$$Min\, f = (p_1, p_2 \ldots . p_n)n \geq 1 \tag{18}$$

each solution's variable reduction optimization function Variables may show specific equality and inequality. Lion has binary structured when n = 1 and an integer for n > 1

$$p_i(p_i^{MIN}, p_i^{MAX}) \tag{19}$$

Four cubs are born from lion-lioness crossing over and mutation. Fig. 3 displays two alternative probabilities of the crossing over. Gender grouping occurs when crossing and mutation produce 4 purebred offspring p^{cub} and 4 mutated offspring p^{new}. The grouping procedure of gender categorization is to produce two result groups, one for p^{m-cub} male infants and one another for p^{f-cub} female infants. Killing unhealthy offspring helps to maintain the overall young population pride. Fig 3. illustrates the various crossover probabilities according to the lion optimization algorithm.

Regional protection and invasion pseudo-code are described in this.

$$(p^{pride}) = \frac{1}{2(1+\| p^{m-cub})}\left(f(p^{male}) + f\,\frac{age^{maturity}}{age(infant)+1}\sum_{z=1}^{p^{m-cub}} \frac{f\left(p_z^{m-infant}\right)+p_z^{f-infant}}{p^{m-cub}}\right) \tag{20}$$

When young lions' offspring reach maturity, they become lions and defend with old-line pride.

After maturing, infants become lions and guard with old-line pride.

During the regional innovation, p^{Male}_{pride} is consist of p^{Male} and p^{infant} and p^{Female}_{pride} consists p^{Female} and $p^{F-infant}$.

$$f\left(p^{Male}_{fittest}\right) < \left(p^{Male}_{fittest}(pd)\right); \left(p^{Male}_{fittest}(pd)\right) \neq p^{Male}_{fittest} \tag{21}$$

$$f\left(p^{Female}_{fittest}\right) < \left(p^{Female}_{fittest}(pd)\right); \left(p^{Female}_{fittest}(pd)\right) \neq p^{Female}_{fittest} \tag{22}$$

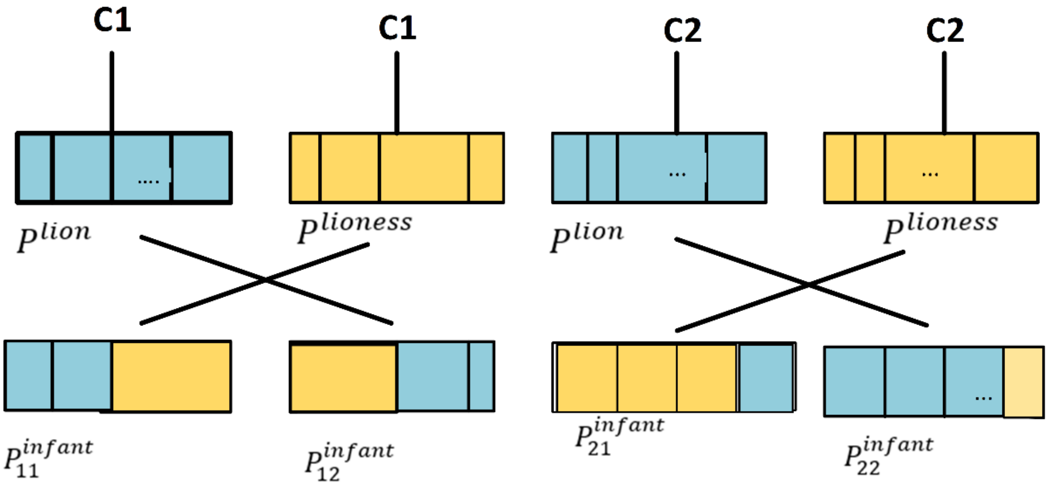

Fig 3. Different crossover probability.

D. *Deer-Hunt optimization(DHO)*

Deer-Hunt Optimization (DHO) is a nature-inspired metaheuristic algorithm based on deer's foraging behavior. It simulates deer's strategies to search for food, incorporating aspects such as exploration and exploitation to find optimal solutions in complex problem spaces. DHO has been effectively applied to various optimization problems, demonstrating robust performance in finding high-quality solutions efficiently[51, 52].

V. RESULT AND ANALYSIS

Simulation and analysis results of effective energy management on SG with IoT by the recommended hybrid system are shown. The suggested hybrid system with DHOLAO algorithm simulated. The obtained simulation findings align with the study objectives of achieving cost-effectiveness, an efficient Peak-to-Average Power Ratio (APR), and a reasonable waiting period. The outcome characteristics of different methods, such as PSO-based support vector machine (SVM), genetic algorithm (GA), crow search optimization (CSO), and deer hunting optimization (DHO) are compared with the introduced method DHOLAO.

The proposed smart grid system is capable of running as a standalone microgrid during the outage. Fig 4 Illustrates the power scheduling and voltage estimations on various nodes of the system. Solar PV, WT, and MT units are engaged simultaneously to maximize the power supply at peak load. Fig. 5 illustrates how the voltage values at various nodes of the grid, and constraints are considered to help restore the voltage within acceptable ranges. In Fig. 6, the voltage adjusts for the original time range (8 p.m.) after the second iteration, but the error persists in the second limits. Finally, the third iteration is shown in Fig. 7 where the voltage set comes with the desirable result. The power comparison analysis of loads 1, 2, and 3 is shown in Fig 8.The charging and discharging of a BESS. The maximum power charging on a BESS using the suggested is 100 kW, which is produced during time frames of 8 to 23 h. The cost analysis between the introduced method and other alternative methods is shown in Fig.9 separately.

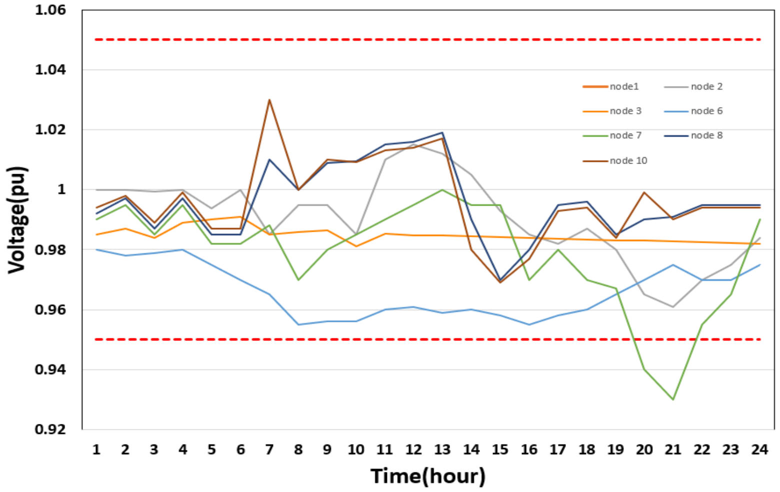

Fig 4. Voltage values at different nodes

A. *Average power demand per day*: Almost every estimation of daily average demand is nearly constant. The power demand is uncontrolled and regulated with different algorithms like GA, CSA, DHOLOA, and ACO are shown in distinct colors. Simulation results are made to compare the efficiency and robustness of the proposed methodology (DHOLAO) and competing algorithms under similar conditions. This similar load determines the most optimal planning approach. This leveled scenario shows APR, energy expenditure, and awaiting duration or consumer discomfort.

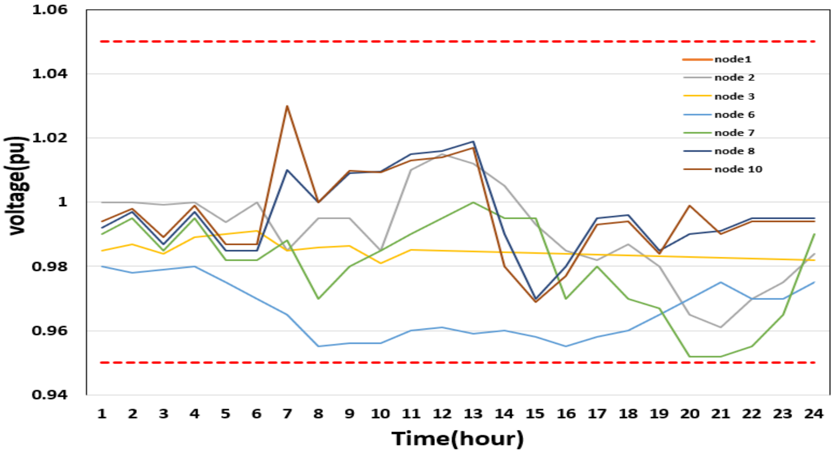

Fig 5. Voltage assessment; Iteration 1

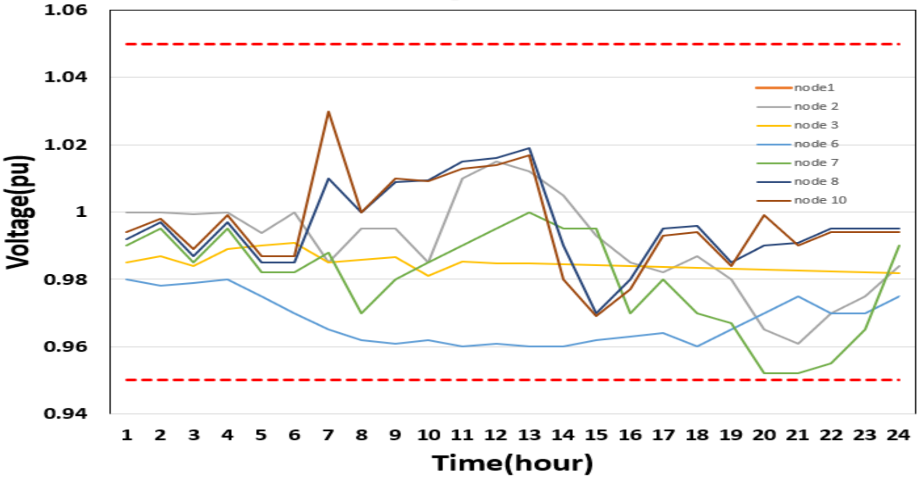

Fig 6. Voltage assessment; Iteration 2

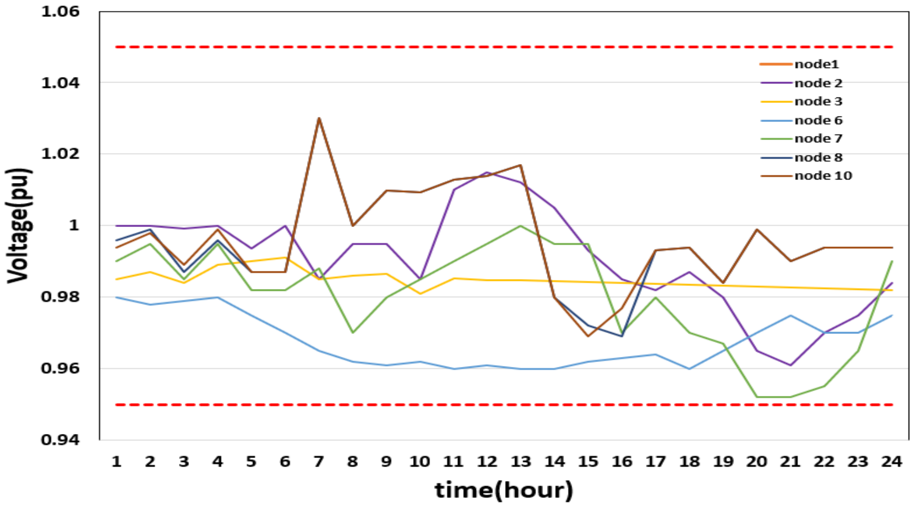

Fig 7. Voltage assessment; Iteration 3

B. *Power demand curves per hour:* Fig. 11 displays hourly power demand curve illustrations for uncontrolled and planned demand employing bio-inspired algorithms such as CSA, ACO, LAO, and GOA. The figure demonstrates that the LA algorithm effectively shifted the demand regions from on-peak to off-peak hours. This approach not only proves to be economically advantageous but also enhances the overall comfort experienced by end-users. This approach yields superior performance with various equipment-rated power and LOTs.

C. *Market signaling alert or DAP:* Many worldwide power infrastructures release day-ahead Real-Time Pricing (RTP) hourly tags. The real-time pricing (RTP) signal provides significant information to both utility companies and customers, enabling them to efficiently track their power utilization. Energy smart meters (SM) send customers information about day-ahead prices(DAP), which helps them plan their everyday demands.

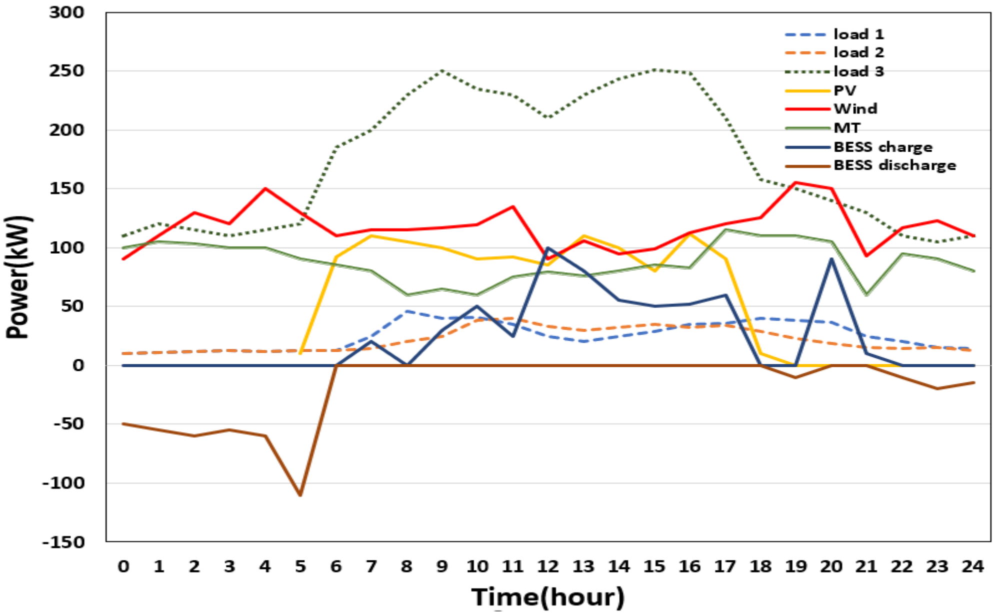

Fig 8. Comparison between hourly power rating of individual entity

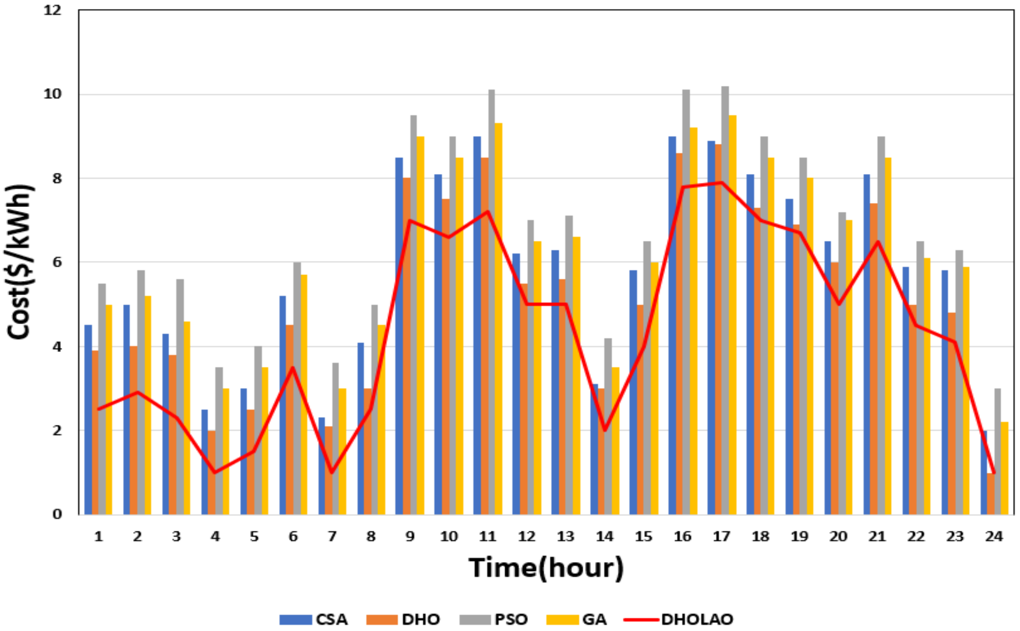

Fig 9. Cost assessment by utilizing CSA, DHO, PSO, GOA, and DHOLAO

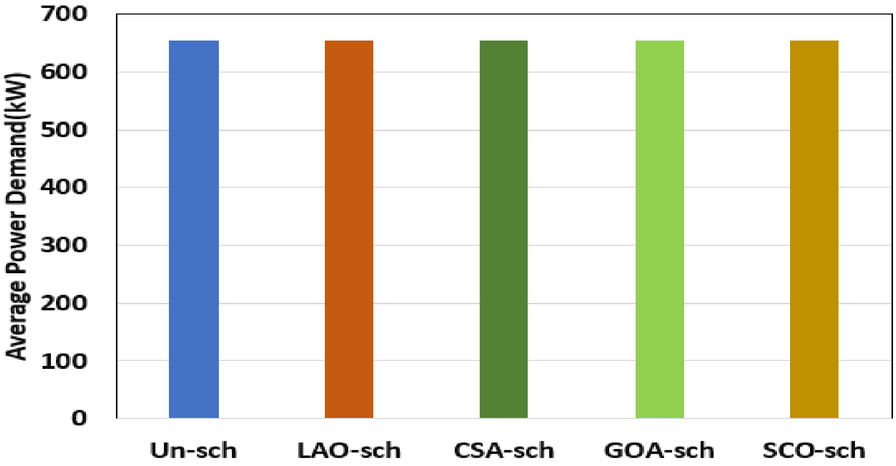

Fig 10. Average power demand per day

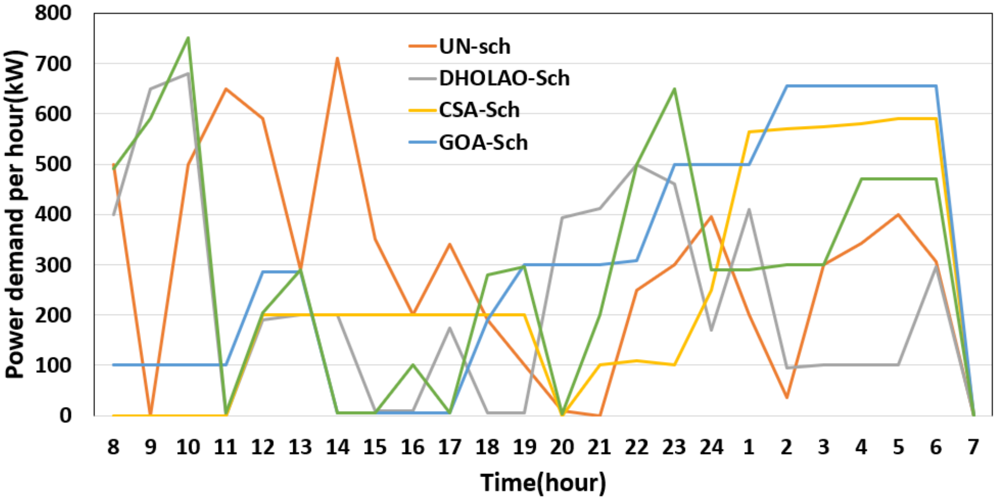

Fig 11. power demand per hour graph

D. *Power costs per hour:* Before determining cumulative power expenditure, estimating hourly cost is important to identify the timespan of high electricity tariffs to improve data scheduling. Fig. 12 shows the different outcomes of different methods. Peaks and dips are visible. DHOLAO provides daily compensation, unlike CSA, GOA, and ACO (24 h). Fig. 13 shows that DHOLAO is able to provide the most cost-effective for everyday power expenditure.

E. *Average power Ratio (APR) Simulation:* The primary focus of researchers is on the consistency of APR in electrical power system. This implies that the stability of the entire system is inversely proportional to the value of PAR, so a relatively small PAR value corresponds to a stable system and vice versa. Fig. 13 shows that the DHOLAO method produces the most stable APR compared to most remaining optimization strategies.

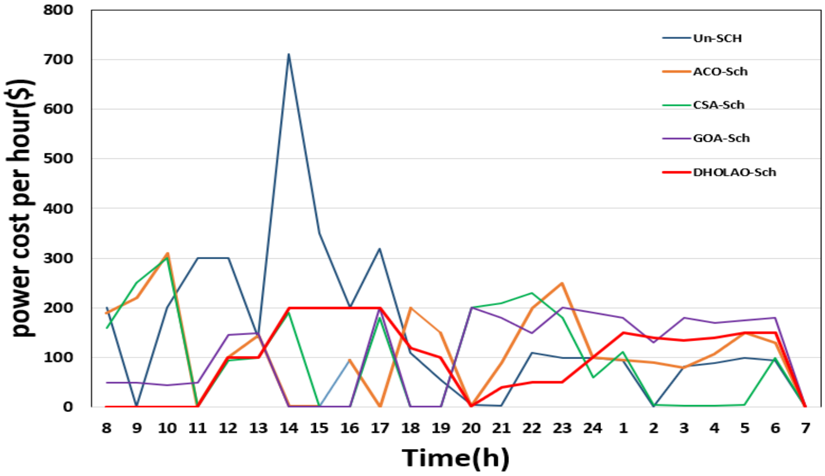

Fig 12. Electricity cost per hour

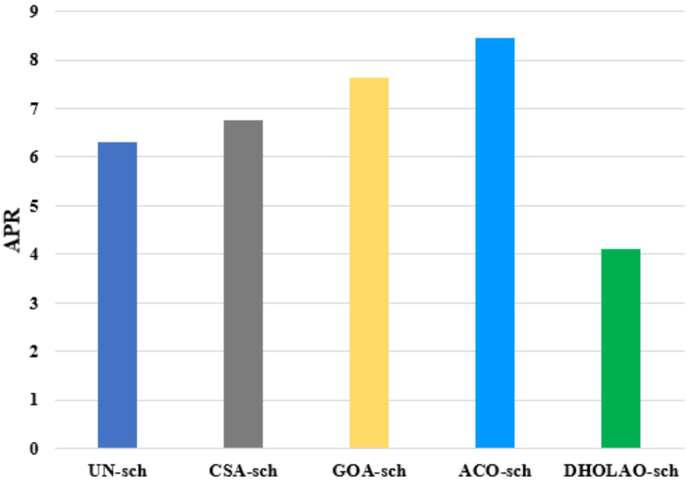

Fig 13. APR graph

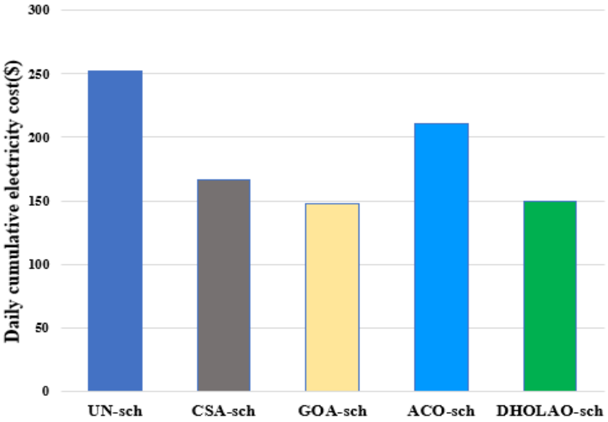

Fig 14. Daily cumulative electricity cost

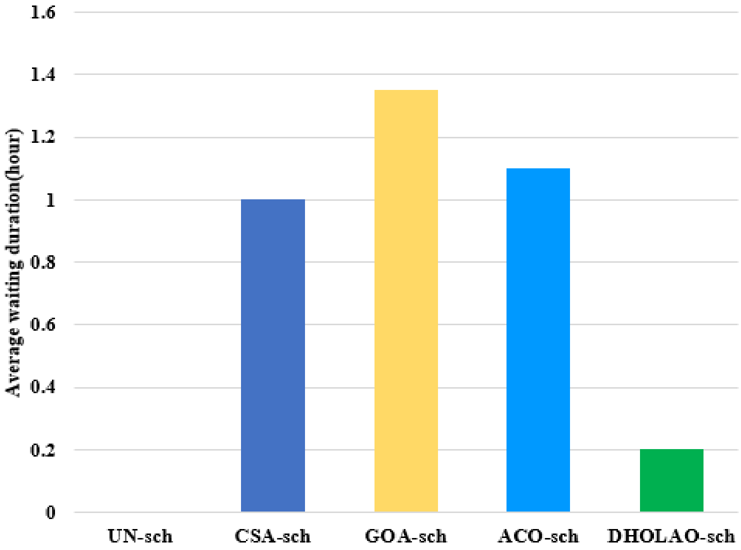

Fig 15. Average waiting duration

F. *Cumulative price of power per day*: Cost optimization is the foremost crucial component for power expense reduction and consumers' electric bills. Performance increases with algorithmic efficiency. According to Fig 15. the GOA optimized expenditure most. Although DHOLAO minimized the overall expenditure with lesser waiting time as displayed in Fig. 14.

G. *Average waiting duration/satisfaction of the consumer:* APR reduction and Cost optimization have a direct impact on the enthusiasm of customers. During scheduling, they worry about demand side awaiting times. During demand-side scheduling, consumer satisfaction is significantly proportional to the device's awaiting duration. Fig. 15 shows the mean awaiting duration of devices by algorithms. As depicted in the illustration, DHOLAO performed better than the remaining methods

VI. CONCLUSION AND THE FUTURE SCOPE

In this article a combination of two bio-inspired algorithms is used named DHOLAO, to design, an optimum EMS for a RES-integrated smart grid with IoT facilities. The proposed HRES consists of solar PV, wind plant, microturbine, BESS, and different kinds of loads. The suggested technique minimizes the hourly cost of electricity, overall energy cost, APR, and consumers' discomfort. The computing time of the algorithms is also estimated and analyzed. In this article, the designed EMS helps to schedule various load areas for optimal energy utilization, and the results are compared with alternative methods such as PSO, CSA, GOA, and ACO. This system is optimized by considering the power demand per hour with different LOTs, dap signal alerts, power cost per hour, average power ratios, and average waiting duration. Thus the introduced method is capable enough to minimize the overall electrical expenditure, consumer discomfort, and computational time as well as stabilize the hourly power demand. In the future, automatic management is also possible for housewares. It may create a change-learning algorithm. It may be able to weather changes seasons and identify seasonal fluctuations in temperature, humidity, and brightness, with the lowest possible demand side waiting time.

CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest in this article.

REFERENCES

[1] Ismagilova, E., Hughes, L., Rana, N. P., & Dwivedi, Y. K. (2022). Security, privacy and risks within smart cities: Literature review and development of a smart city interaction framework. Information Systems Frontiers, 24(2), 393-414.

[2] Haque, A. B., Bhushan, B., & Dhiman, G. (2022). Conceptualizing smart city applications: Requirements, architecture, security issues, and emerging trends. Expert Systems, 39(5), e12753.

[3] Al-Turjman, F., Zahmatkesh, H., & Shahroze, R. (2022). An overview of security and privacy in smart cities' IoT communications. Transactions on Emerging Telecommunications Technologies, 33(3), e3677.

[4] Muhammad G, Alshehri F, Karray F, et al. A comprehensive survey on multimodal medical signals fusion for smart healthcare systems. Inf Fusion 2021;77:355–75.

[5] Rathor, S. K., & Saxena, D. (2020). Energy management system for smart grid: An overview and key issues. International Journal of Energy Research, 44(6), 4067-4109.

[6] Singh, A. R., Ding, L., Raju, D. K., Kumar, R. S., & Raghav, L. P. (2021). Demand response of grid-connected microgrid based on metaheuristic optimization algorithm. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 1-22

[7] Rahmani, R., Moser, I., & Cricenti, A. L. (2020). Modeling and optimization of microgrid configuration for green data centers: A metaheuristic approach. Future Generation Computer Systems, 108, 742-750.

[8] Jayalakshmi, N. S., Jadoun, V. K., Gaonkar, D. N., Shrivastava, A., Kanwar, N., & Nandini, K. K. (2022). Optimal operation of a multi-source electric vehicle connected microgrid using metaheuristic algorithm. Journal of Energy Storage, 52, 105067.

[9] Rizvi, M., Pratap, B., & Singh, S. B. (2022). Optimal energy management in a microgrid under uncertainties using novel hybrid metaheuristic algorithm. Sustainable Computing: Informatics and Systems, 36, 100819. https://doi.org/10.1016/j.suscom.2022.100819

[10] Hossain, M. A., Chakrabortty, R. K., Ryan, M. J., & Pota, H. R. (2021). Energy management of community energy storage in grid-connected microgrid under uncertain real-time prices. Sustainable Cities and Society, 66, 102658.

[11] Pal, S., Thakur, S., Kumar, R., & Panigrahi, B. K. (2018). A strategical game theoretic based demand response model for residential consumers in a fair environment. International Journal of Electrical Power & Energy Systems, 97, 201-210.

[12] Luna, A. C., Diaz, N. L., Graells, M., Vasquez, J. C., & Guerrero, J. M. (2016). Mixed-integer-linear-programming-based energy management system for hybrid PV-wind-battery microgrids: Modeling, design, and experimental verification. IEEE Transactions on Power Electronics, 32(4), 2769-2783.

[13] Shakeri, M., Shayestegan, M., Reza, S. S., Yahya, I., Bais, B., Akhtaruzzaman, M., ... & Amin, N. (2018). Implementation of a novel home energy management system (HEMS) architecture with solar photovoltaic system as supplementary source. Renewable energy, 125, 108-120.

[14] Ullah, I., Hussain, I., Rehman, K., Wróblewski, P., Lewicki, W., & Kavin, B. P. (2022). Exploiting the moth–flame optimization algorithm for optimal load management of the university campus: A viable approach in the academia sector. Energies, 15(10), 3741.

[15] Hafeez, G., Wadud, Z., Khan, I. U., Khan, I., Shafiq, Z., Usman, M., & Khan, M. U. A. (2020). Efficient energy management of IoT-enabled smart homes under price-based demand response program in smart grid. Sensors, 20(11), 3155.

[16] Boothalingam, R. (2018). Optimization using lion algorithm: a biological inspiration from lion's social behavior. Evolutionary Intelligence, 11(1), 31-52.

[17] Aslam S, Bukhsh R, Khalid A, Javaid N, Ullah I, Fatima I, Hasan QU. An efficient home energy management scheme using cuckoo search. In International Conference on P2P, Parallel, Grid, Cloud and Internet Computing. Springer; 2017. pp. 167–178.

[18] Wen Z, O'Neill D, Maei H. Optimal demand response using device-based reinforcement learning. IEEE Trans Smart Grid 2015;6:2312–24.

[19] Erol-Kantarci M, Mouftah HT. Energy-efficient information and communication infrastructures in the smart grid: A survey on interactions and open issues. IEEE Commun Surveys Tutor 2014;17:179–97.

[20] El-Zonkoly A. Optimal placement of multi-distributed generation units including different load models using particle swarm optimisation. IET Gener Transmission Distrib 2011;5:760–71

[21] Safdarian A, Fotuhi-Firuzabad M, Lehtonen M. Optimal residential load management in smart grids: A decentralized framework. IEEE Trans Smart Grid 2015;7:1836–45.

[22] Jindal, A., Aujla, G. S., Kumar, N., & Villari, M. (2019). GUARDIAN: Blockchain-based secure demand response management in smart grid system. IEEE transactions on services computing, 13(4), 613-624.

[23] Christopher, S. B., & Mabel, M. C. (2020). A bio-inspired approach for probabilistic energy management of micro-grid incorporating uncertainty in statistical cost estimation. Energy, 203, 117810.

[24] Wagle, R., Sharma, P., Sharma, C., Gjengedal, T., & Pradhan, C. (2021). Bio-inspired hybrid BFOA-PSO algorithm-based reactive power controller in a standalone wind-diesel power system. International Transactions on Electrical Energy Systems, 31(3), e12778.

[25] Khan, F. A., Ullah, K., ur Rahman, A., & Anwar, S. (2023). Energy optimization in smart urban buildings using bio-inspired ant colony optimization. Soft Computing, 27(2), 973-989.

[26] Al Duhayyim, M., Eltahir, M. M., Al-Wesabi, F. N., Hilal, A. M., Al-Yarimi, F. A. M., Hamza, M. A., ... & Wesabi, F. N. (2022). Intelligent Deer Hunting Optimization Based Grid Scheduling Scheme. CMC-COMPUTERS MATERIALS & CONTINUA, 72(1), 181-195.

[27] Tian, M. W., Yan, S. R., Han, S. Z., Nojavan, S., Jermsittiparsert, K., & Razmjooy, N. (2020). New optimal design for a hybrid solar chimney, solid oxide electrolysis and fuel cell based on improved deer hunting optimization algorithm. Journal of Cleaner Production, 249, 119414.

[28] Qays, M. O., Ahmad, I., Abu-Siada, A., Hossain, M. L., & Yasmin, F. (2023). A review of key communication technologies, applications, protocols, and future guides for IoT-assisted smart grid systems. Energy Reports, 9, 2440-2452.

[29] Khan, A. A., Laghari, A. A., Rashid, M., Li, H., Javed, A. R., & Gadekallu, T. R. (2023). Artificial intelligence and blockchain technology for secure smart grid and power distribution Automation: A State-of-the-Art Review. Sustainable Energy Technologies and Assessments, 57, 103282.

[30] Olatunde, T. M., Okwandu, A. C., Akande, D. O., & Sikhakhane, Z. Q. (2024). The impact of smart grids on energy efficiency: a comprehensive review. Engineering Science & Technology Journal, 5(4), 1257-1269.

[31] Vritti, V., Garg, K. D., Sood, V. M., & Narang, S. K. (2024). Energy Management in IoT-Enabled Smart Grid: A Review. Artificial Intelligence and Society 5.0, 118-132.

[32] Mazhar, T., Irfan, H. M., Haq, I., Ullah, I., Ashraf, M., Shloul, T. A., ... & Elkamchouchi, D. H. (2023). Analysis of challenges and solutions of IoT in smart grids using AI and machine learning techniques: A review. Electronics, 12(1), 242.

[33] Abir, S. A. A., Anwar, A., Choi, J., & Kayes, A. S. M. (2021). Iot-enabled smart energy grid: Applications and challenges. IEEE Access, 9, 50961-50981.

[34] Khalid, M. (2024). Smart grids and renewable energy systems: Perspectives and grid integration challenges. Energy Strategy Reviews, 51, 101299.

[35] Lawal, K., & Rafsanjani, H. N. (2022). Trends, benefits, risks, and challenges of IoT implementation in residential and commercial buildings. Energy and Built Environment, 3(3), 251-266.

[36] Tabaa, M., Monteiro, F., Bensag, H., & Dandache, A. (2020). Green Industrial Internet of Things from a smart industry perspective. Energy Reports, 6, 430-446.

[37] Umair, M., Cheema, M. A., Cheema, O., Li, H., & Lu, H. (2021). Impact of COVID-19 on IoT adoption in healthcare, smart homes, smart buildings, smart cities, transportation, and industrial IoT. Sensors, 21(11), 3838.

[38] Munirathinam, S. (2020). Industry 4.0: Industrial internet of things (IIOT). In Advances in Computers (Vol. 117, No. 1, pp. 129-164). Elsevier.

[39] Nagaty, K. A. (2023). IoT commercial and industrial applications and AI-powered IoT. In Frontiers of Quality Electronic Design (QED) AI, IoT and Hardware Security (pp. 465-500). Cham: Springer International Publishing.

[40] Syamala, M., Komala, C. R., Pramila, P. V., Dash, S., Meenakshi, S., & Boopathi, S. (2023). Machine Learning-Integrated IoT-Based Smart Home Energy Management System. In Handbook of Research on Deep Learning Techniques for Cloud-Based Industrial IoT (pp. 219-235). IGI Global.

[41] Saleem, M. U., Shakir, M., Usman, M. R., Bajwa, M. H. T., Shabbir, N., Shams Ghahfarokhi, P., & Daniel, K. (2023). Integrating smart energy management systems with the Internet of Things and cloud computing will be beneficial for efficient demand-side management in smart grids. Energies, 16(12), 4835.

[42] Afonaa-Mensah, S., Odoi-Yorke, F., & Majeed, I. B. (2024). Evaluating the impact of industrial loads on the performance of solar PV/diesel hybrid renewable energy systems for rural electrification in Ghana. Energy Conversion and Management: X, 21, 100525.

[43] Marudaipillai, S. K., Karuppudayar Ramaraj, B., Kottala, R. K., & Lakshmanan, M. (2023). Experimental study on thermal management and performance improvement of solar PV panel cooling using form-stable phase change material. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 45(1), 160-177.

[44] Basak, S., & Bhattacharyya, B. (2023). Optimal scheduling in demand-side management based on a grid-connected microgrid system by a hybrid optimization approach that considers diverse wind profiles. ISA transactions, 139, 357-375.

[45] Nargeszar, A., Ghaedi, A., Nafar, M., & Simab, M. (2023). Reliability evaluation of the renewable energy-based microgrids considering resource variation. IET Renewable Power Generation, 17(3), 507-527.

[46] Gbadega, P. A., & Sun, Y. X. (2023). JAYA algorithm-based energy management for a grid-connected micro-grid with PV-wind-microturbine-storage energy system. International Journal of Engineering Research in Africa, 63, 159-184.

[47] Velani, M., Chhabhaiya, V., Bhadani, R., & Thumbar, S. (2024). Introduction to Optimization Techniques for Microgrid. In Microgrid (pp. 25-50). CRC Press.

[48] Cao, T., Hwang, Y., & Radermacher, R. (2017). Development of an optimization based design framework for microgrid energy systems. Energy, 140, 340-351.

[49] Fathy, A., & Abdelaziz, A. Y. (2018). Single and multi-objective operation management of micro-grid using krill herd optimization and ant lion optimizer algorithms. International Journal of Energy and Environmental Engineering, 9, 257-271.

[50] Nallolla, C. A., P, V., Chittathuru, D., & Padmanaban, S. (2023). Multi-objective optimization algorithms for a hybrid AC/DC microgrid using RES: A comprehensive review. Electronics, 12(4), 1062.

[51] Brammya, G., Praveena, S., Ninu Preetha, N. S., Ramya, R., Rajakumar, B. R., & Binu, D. (2019). Deer hunting optimization algorithm: a new nature-inspired meta-heuristic paradigm. The Computer Journal, bxy133.

[52] Yuan, Z., Wang, W., Wang, H., & Ashourian, M. (2020). Parameter identification of PEMFC based on Convolutional neural network optimized by balanced deer hunting optimization algorithm. Energy Reports, 6, 1572-1580.