Optimal Sitting and Sizing of Renewable Energy Sources and Electric Vehicle Charging Stations in Smart Grids Using COA Approach

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Abstract: Electric vehicles (EVs) and renewable energy sources (RES) provide unpredictability to power networks that can affect network performance and cause problems including voltage swings, increased power losses, and poorer power quality. In order to overcome these obstacles and guarantee dependable network functioning, it is essential to properly account for the varying production from RES and the extra demand from EV charging. This manuscript proposes an optimal sitting and sizing of RES and EVCS in smart grids using COA approach. The proposed method is Crayfish Optimization Algorithm (COA). The proposed method's primary goal is to reduce power losses, voltage variations, demand supply and charging expenses, and EV battery costs. The proposed COA algorithm is used to solve the optimization problem of RES and EVCS simultaneously in smart grids. By then, the MATLAB working platform has the proposed framework implemented, and the current methods are used to compute the execution. The proposed technique is compare with all existing method like Backtracking Search Algorithm (BSA), and Particle Swarm Optimization (PSO). From the result, it is clued that the proposed method shows the voltage fluctuations and power loss is low.

Keywords: Electric vehicle, Photovoltaic, Wind Turbine, EV charging Station, Green House Gas, Smart Grid.

1. Introduction

In view of the substantial Greenhouse Gas emissions from the transportation sector, EV adoption is rising quickly throughout many nations as a more environmentally friendly substitute for combustion EV with the goal of lowering GHG emissions [1-2]. This trend is further fueled by the depletion of petroleum resources and environmental concerns. EVs, known for being quiet, safe, emission-free, and energy-efficient, are becoming more prevalent. In addition to having positive effects on the environment, their utilization helps the electrical distribution network by supporting voltage and frequency control and serving as spinning reserves [3]. On the other hand, poor EV integration into the distribution network can result in problems including higher power losses, decreased power quality, and voltage variations. To address these challenges, Distributed Generation (DG) can be integrated into the network [4]. Among DG options, Photovoltaic (PV) systems stand out due to decreasing costs of photovoltaic panels and accessories, in addition to the abundance of solar energy. Over 70 GW of PV systems are installed annually worldwide [5]. As PV systems can maintain voltage and reduce peak shaving, they can lessen the detrimental effects that EVs have on the distribution network.

Recent studies indicate that parked and plugged-in Electric Vehicles (EVs) in metropolitan areas can serve as a rapid power storage resource [6]. The energy density of EV batteries has significantly increased during the last several years, with millions of ESCs worldwide currently using 80–100 kWh batteries [7]. These days, electric vehicles may serve as peaking plants by contributing energy to the grid at peak hours in addition to consuming it for charging. With the

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use of this idea, called the Vehicle-to-Grid (V2G) system, EVs can help fulfill peak energy needs [8–9]. However, a high number of EV charging events within a short timeframe can lead to a sharp increase in grid load, causing voltage fluctuations and impacting power system stability [10]. Therefore, establishing an interactive link between the distribution network and EV charging facilities is crucial in the current planning of EV charging infrastructure. The load from charging stations can help boost the consumption of RE and mitigate the uneven distribution of distributed energy [11]. Enhancing power quality by utilizing the complimentary advantages of several resources will eventually guarantee the dependability and stability of the distribution network system [12].

Typically, V2G operations are carried out by dedicated mega chargers with high-capacity inverters, or utilizing the built-in inverters in EVs while they are parked at charging stations [13–14]. A group of contemporary EVs operating as dispersed energy sources can supply the grid with power backup in the megawatt (MW) range [15]. Reliance on traditional fossil fuels can be decreased by increasing the integration of RES into traditional power and transportation networks [16]. However, the unpredictable nature of renewable energy can cause power grid instability and potential failures, limiting their widespread adoption. To address this issue, a larger deployment of EVs can help safely integrate intermittent RE into the grid [17]. By storing extra renewable energy for eventual injection into the grid during times of high demand, these EVs can function as distributed ESS minimizing the waste of renewable energy [18]. This approach can also decrease reliance on fossil fuels and costly spinning reserve generators. Renewable Energy is increasingly incorporated into SGs, efficient algorithms become increasingly important in guaranteeing the reliable and efficient operation of the entire grid [19]. Global researchers are searching for trustworthy methods to leverage EVs and other energy storage technologies to boost power output from intermittent sources [20].

E A Rene et al. [21] have demonstrated how to discover the ideal positions for PEVCS at certain busses in a network of distribution with high levels of distributed generation (DG) by using a hybrid GA-PSO approach. The research made use of distributed generation in the form of photovoltaic (PV) systems, which run at a power factor of 0.95. Six distinct penetration scenarios were taken into consideration for the strategic placement of PEVCSs, and 60% of the PV systems were included into the network of distribution. The multi-objective optimization goal was determined to be the voltage variation index as well as, loss of power in both active and reactive modes. The investigation employed the IEEE 33 and 69 bus distribution networks. Balu and V Mukherjee [22] In order to ascertain the best location for EVBSS and EVCS in the Radial Distribution System (RDS), a new methodology has been devised. Modeled as a continuous current load was the EV charger. Distinct various load types, including industrial, commercial, domestic, and steady power, were used to examine the impacts of the EVCS and EVBSS demand on various aspects, such as voltage profile, total voltage variance, actual power loss, energy loss expense, and overall RDS operating cost. For the network to be more reliable and self-sustaining, it was essential to add DGs of the ideal size at strategic locations within the RDS to lessen the effects of EVCS and EVBSS loads. Additionally, in order to increase the system's overall efficiency and dependability, non-dispatchable PV and WT units were combined with battery energy storage (BES) to become dispatchable units. A Eid et al. [23] they have implemented the distribution systems were designed to include different RES, such WT and PV units, in addition to EVCS placed at particular points in the distribution network. BES was strategically placed alongside the WT and PV units to facilitate power control within the system, aiming to improve overall performance by minimizing defined fitness functions. Whether a BES unit was producing or consuming power, its operation was mostly determined by its SoC and system constraints. To solve the optimization problem, the Gorilla Troop Optimizer (GTO) approach was applied as a single-objective strategy. Reducing the overall voltage variation and power loss in the 108-bus distribution system was the main goal of the optimization. Using the GTO approach in two phases allowed for the effective solution of the optimization issue.

N O Aljehane and R F Mansour [24] have suggested a new approach combining deep learning with metaheuristic optimization was developed for the distribution of RES-CS for PHEVs. The model utilized MPC to manage real-time energy based on the actual battery SoC . The BWO method, which developed objective functions taking into account numerous charging station metrics, was used to optimize the allocation of RES/CS.Additionally, the DSAE was employed within the MPC framework to predict near-future vehicle velocity. K Kalaiselvan et al. [25] demonstrated an MG system that was created by combining modest hydropower and solar PV sources. The MG is grid-connected and has an autonomous electric car charging system integrated into it.For MG systems, a hybrid control strategy called the GOA-THDCNN approach—a combination of the GOA and THDCNN—was presented. The goal of this strategy is to manage microgrid systems effectively. Three primary goals guided the technique's conception. Initially, it focuses on optimizing power consumption and enhancing excitation efficiency by managing grid-tied loads via a hybrid PV network injection. Second, it aims to facilitate smart distribution collaboration through the use of a decentralized system that engages with micro-energy grid integration and assures network power support. In order to maximize operational efficiency, this integration combines Photovoltic and hydropower resources for charging electric vehicles. MPPT and management are also used. A K Mohanty and S B Perli [26] have presented a brand-new Battle Royal Optimization (BR v O) algorithm that makes use of fuzzy multi-objective functions to place EVCS, DGs, and shunted capacitors in a 69-bus RDS in the best possible way both simultaneously and in two stages. The major goals of the method were to decrease active power loss, raise the substation power factor, increase the voltage profile of the distribution network, and optimize the distribution of cars among CS. Additionally, the effectiveness of the introduced system was demonstrated under increased electric vehicle demand and distribution system loads. U u Rehman [27] have demonstrated a brand-new, very effective hierarchical bi-directional aggregation method that was created to integrate EVs into the SG via a network of CS and V2G technology. The proposed method estimates power usage and applies Day-ahead load scheduling in the SG by streamlining EV charging and discharging activities. This technique maintains the voltage and frequency of the SG by using EVs and recharge stations as instruments. Prior to integrating EVs in V2G mode, the algorithm determines the cost of battery deterioration prior to starting charging, collects projected parking and departure time data from EV owners, and rates the SoC of EVs upon arriving at the CS. When the owner requests it, the algorithm gathers all pertinent data and uses the EV in V2G mode to control the SG, guaranteeing the intended SoC level when the owner departs.

2. Configuration of EV Charging Stations and Renewable Energy Sources in Smart Grid

Configuration of EVCS and RES in smart grid is shown in Fig 1. Here, the electricity consumption sources such as solar PV, battery, and WT. Then the consumed electricity is given to smart grid. The SG can then be used to distribute the electricity to load and EVCS. The optimization issue for RES and EVCS is solved by applying the proposed COA method.

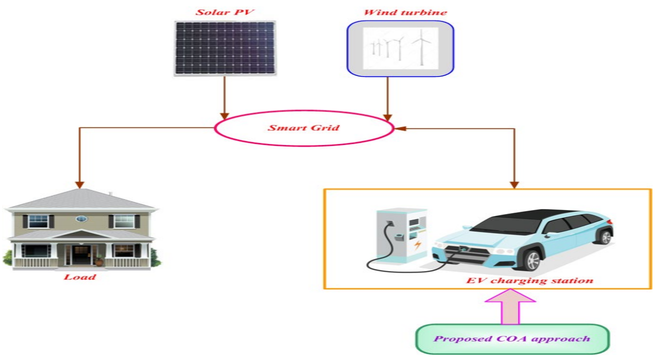

Figure 1. Configuration of EVCS and RES in smart grid

A. Modelling of PV

Solar energy is captured by the PV panel, which produces the electricity. Heat is produced when most solar energy strikes the PV panels instead of being converted to electricity [28]. Therefore, the effect of temperature and The impact of solar radiation on output power is taken into account. The output of a single photovoltaic panel is specified as follows:

$$P_{sol}(t) = \frac{P_n S_n}{1000}[1 - \lambda(L_{cell} - 25)] \tag{1}$$

Wherever, indicates solar energy.

The cell's temperature and the power fluctuation in response to temperature changes are supplied by:

$$L_{cell} = L_{amb} + \frac{NOCT - 20}{0.8} S_n \tag{2}$$

Here, °C is the ambient temperature, and kW/m2 of solar radiation is present, the cell temperature, which is the temperature at which power must be estimated, is represented by the characters and respectively.

The maximum output power rating is intended to be as:

$$P_n = V_n I_n \tag{3}$$

Where and indicates extreme voltage and current ratings. Further, the formula used to determine the total power produced by PV panels is:

$$P_{PV}(t) = N_{PV} P_{sol}(t) \tag{4}$$

Here, the number of PV panels is.

B. Modelling of Wind Turbines

A WT power output is determined by the wind's velocity and the region it blows across. One may compute the power derived by a WT as follows:

$$P_{WT}(T) = \begin{cases} 0 & A(T) \le A_{cin} \; or \; A(T) \ge A_{coff} \\ P_R^W \dfrac{A(T) - A_{cin}}{A_R - A_{cin}} & A_{cin} < A(T) < A_R \\ P_R^W & A_R \le A(T) < A_{coff} \end{cases} \tag{5}$$

Here, represents the WT's rated power, indicates the specified wind speed, indicates the cut-in speed, represeneed, and indicates the needed height of the wind speed.

An illustration of wind speed throughout the year is a probability density function (PDF), which is a curve. Plotting a curve with changing wind speeds takes into account that the likelihood that the wind will be between two speeds is represented by the area under the curve. It is able to be stated as:

$$P(a_1 \le a \le a_2) = \int_{a_1}^{a_2} E_a da \tag{6}$$

$$P(0 \le a \le \infty) = \int_0^{\infty} E_a da = 1 \tag{7}$$

Where, E_a is the wind speed PDF, and are the two wind speeds.

The Weibull probability function is the most significant PDF in wind speed statistics. The definition of the Weibull probability function, which serves as the foundation for defining wind speed statistics, is as follows:

$$E_a = \frac{k}{c}\left(\frac{a}{c}\right)^{k-1} \exp\left(\left(-\frac{a}{c}\right)^k\right) \tag{8}$$

Here, k indicates the shape parameter, c represents the scale parameter, and a repersents the wind speed.

$$A = A_0 \left(\frac{H_{wt}}{H_0} \right)^{\alpha} \tag{9}$$

Here, A represents the wind speed at a required height H_{wt} , the wind speed at a reference height H_o is indicated by A_o and ά indicates friction coefficient. The surface that the wind is blowing across affects the friction coefficient. For the most part, 1/7 is thought to be an approximate figure for ά.

The whole power produced by wind turbines (is computed as :

$$P_{wt}(T) = N_{wt} P_{WT}(T) \tag{10}$$

Here, represents the number of WTs.

C. Modelling of EV Charging Stations

Based on their SoC, which is the ratio of a battery's maximum capacity to its useable capacity at full charge, EVs may be charged. It therefore displays the proportion of battery charge that is still present.

The practical limitations placed on EV charging can be expressed mathematically as follows:

$$SoC_{\min} \le SoC(t) \le SoC_{\max} \tag{11}$$

$$D_{rate}(t) \le D_{rate}^{\max} \tag{12}$$

Here, is the minimum SoC value, is the maximum SoC value, represents the current SoC value for a certain EV at a specific moment, indicates the EV's current charging rate, and indicates the EVs' maximum permitted charging rate.

The power of the EVs at the CS is computed as follows at each given instant t:

$$P_{EV}(t) = \frac{E_{\max} \cdot SoC(t)}{100\,\Delta t} \tag{13}$$

Here, $E_{\max}$ represents the maximum energy capacity of the vehicle, Δt indicates the time interval considered as one hour.

By comparing an EV's SoC with SoC_{cr} , the crucial SoC, one may ascertain how different their charging requirements are from one another.

D. Objective Function

Power loss minimization [29],

$$P_{Loss} = \sum_{t=1}^{24} \sum_{k=1}^{NB} \sum_{i>1}^{NB} Z_{ki} \left[v_{k,t}^2 + v_{i,t}^2 + 2 v_{k,t} v_{i,t} \cos\left(\delta_{k,t} - \delta_{i,t} \right) \right] \tag{14}$$

Here, Z_{ki} is the ki^{th} element of the admission bus matrix Z and NB is the total number of network buses. t is the time indices, k, i is the bus indices, P_{Loss} is the active power loss.

3. Optimizing EV Charging Stations with Renewable Energy Sources Based on COA Approach

A. Algorithm of Crayfish Optimization

The COA is discussed here. The crayfish resembles a shrimp, boasting a notably tough shell. Taxonomically, it falls under the categories of Arthropod, Crustacean, and Decapods. Widely regarded as a vital species within freshwater environments, crayfish inhabit diverse ecosystems include lakes, rivers, streams, cave pools, ephemeral ponds, and periodically inundated fields [30]. They excavate burrows to evade natural predators and cope with summertime heat. Additionally, crayfish are characterized as aquatic animals capable of enduring a broad range of temperatures.

Step 1 : Initialization
Set all of the input parameters, including voltage, power, and current, to zero.

Step 2 : Random Generation
The initialized populations are arbitrarily generated by using arbitrary generation, which is described by,

$$X = \begin{bmatrix} X_{1,1} & X_{1,j} & X_{1,\dim} \\ X_{i,1} & X_{i,j} & X_{i,\dim} \\ X_{N,1} & X_{N,j} & X_{N,\dim} \end{bmatrix} \tag{15}$$

Here, the starting population position is represented by X, N represents the number of populations, $\dim$ denotes the population dimension,' $X_{i,j}$ represents the location of individual i in the j dimension. and the $X_{i,j}$ value is achieved. N stands for the number of populations, $\dim$ for the population dimension, and $X_{i,j}$ for the individual's placement i inside the j dimension. and the value of $X_{i,j}$ is attained.

Step 3 : Fitness Evaluation
The fitness value F is evaluated by,

$$F = Min(D) \tag{16}$$

Where, D is the objective function for cost of battery.

Step 4 : Exploration Phase
When the temperature increases, $temp > 30$. For their summer vacation, the crayfish will now choose to stay within the cave. Below is a description of the cave X_{shade}:

$$X_{shade} = (X_G + X_L)/2, \tag{17}$$

Here, X_L denotes the ideal location of the existing population and Based on the quantity of repetitions, X_G denotes the best position attained thus far.

Step 5 : Exploitation Phase
When $temp > 30$ and $rand\,30 \geq 0.5$, appear, it suggests that more crayfish are interested in the cave. They are going to fight to take the cave immediately.

$$X_{i,j}^{t+1} = X_{i,j}^{t} - X_{z,j}^{t} + X_{shade,} \tag{18}$$

Here, z stands for the crayfish random individual, as demonstrated by Eqn (19):

$$z = round(rand \times (N-1)) + 1. \tag{19}$$

During the Competition stage, crayfish compete with one another. Crayfish X_i changes its location in reaction to X_z, another crayfish. The location can be altered to increase the COA's search area and improve the algorithm's capacity for investigation.

Step 6 : Update the Best solution
Condition has been updated based on the first and second phases, an iteration of the COA is considered complete.

Step 7 : Termination Criteria
If the solution is the best, the procedure is terminate; if not, it is go back to the step 3 fitness evaluations and continue processing the next stages until a solution is found.

B. Flowchart of Crayfish Optimization :

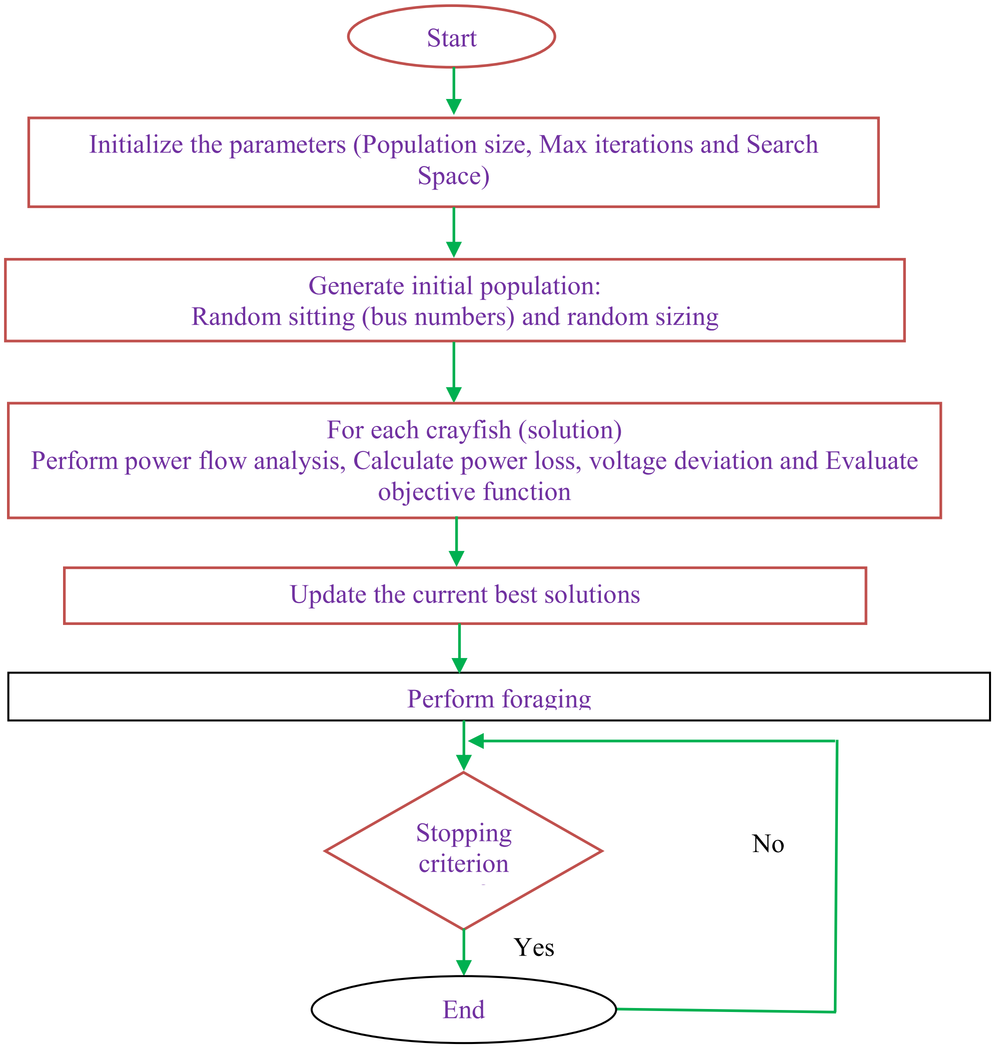

Figure 2. Flow chart of Crayfish Algorithm

4. Result and Discussion

This part provides an illustration of how the proposed method performed based on the results of the simulation. The RES and EVCS in this paper, the COA approach is proposed. The objective of this proposed technique is to decrease the cost of EV batteries, power losses, voltage variations, and demand and supply expenses. IEEE 33 bus technology shown in Fig 3 is used to test the proposed method.

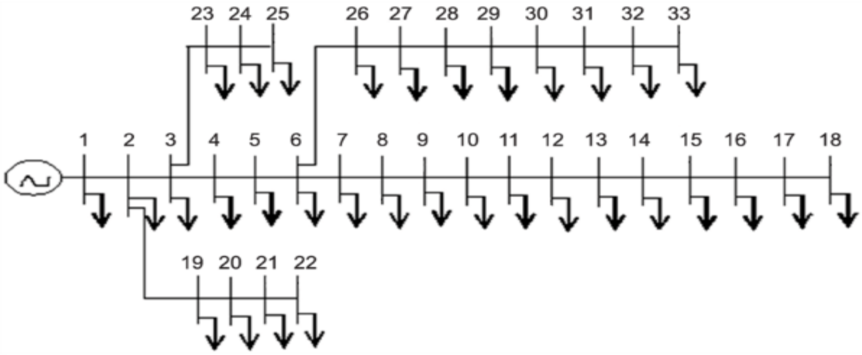

Figure 3. IEEE 33 Bus System

Initially voltage at node 1 is 1 p.u.when EV charging station load is applied to the system , the volatge reduces which is shown in Fig 4.At node 18 , minimum voltage occurs. The value is 0.8944 p.u for load condition , 0.8988 p.u under normal condition , by applying COA the volatge at node 18 is 0.9176 p.u.Fig 5 compares bus voltages for all the algorithms like PSO,BSA and COA algorithms.From the Fig 5 it is shows that COA algorithm gives better results as compared to remaining algorithm. The analysis of Figures 4 and 5 confirms that the COA algorithm not only improves voltage levels under EV charging load but also outperforms other techniques like PSO and BSA. This makes it a strong candidate for voltage stability enhancement and loss minimization in distribution systems with EV and renewable energy integration.

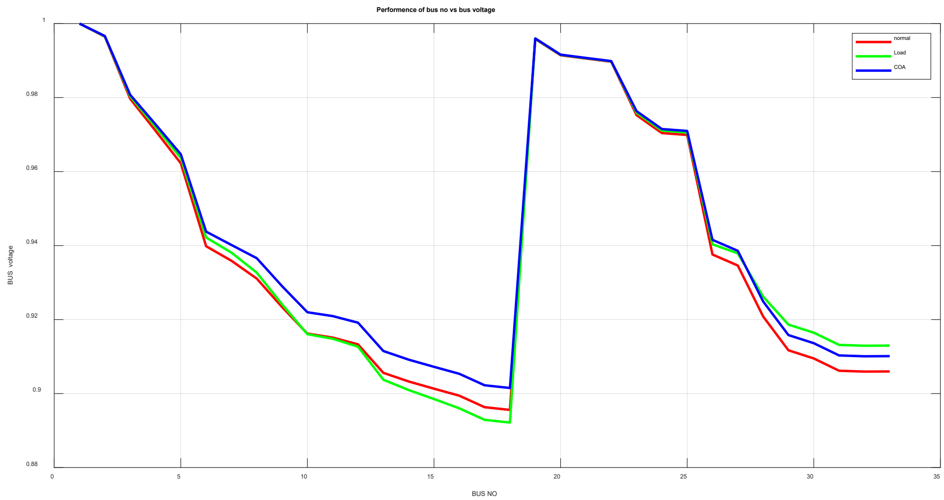

Figure 4. Bus Voltage of IEEE 33-bus system using COA algorithm.

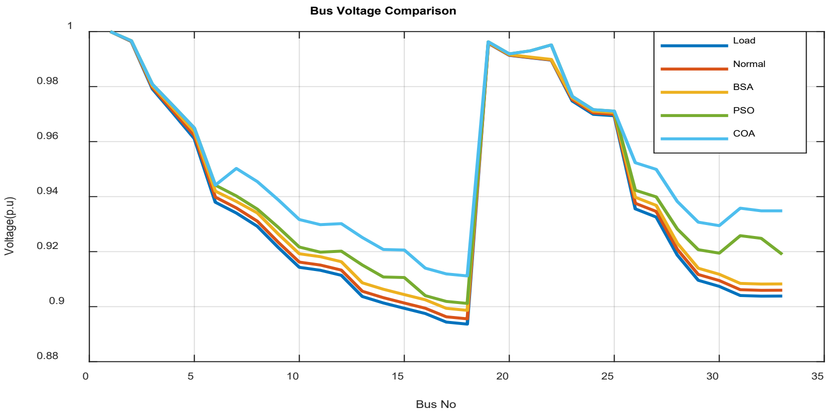

Figure 5. Bus Voltage Comparison of IEEE 33-bus system using diffrent algorithms.

Fig 6 illustrates the comparison of bus voltage profiles under Load-2 conditions using different optimization algorithms, namely PSO, BSA, and COA. The Crayfish Optimization Algorithm (COA) demonstrates superior performance by maintaining higher voltage levels across the majority of buses, particularly in low-voltage areas. The improvement in voltage profile confirms that COA ensures better voltage stability and more effective load balancing under increased system stress due to Load-2, compared to PSO and BSA. Fig 7 compares the total real power losses obtained from different algorithms. Among the tested techniques, the COA algorithm results in the lowest power loss, indicating a more efficient power flow and reduced transmission losses. This improvement can be attributed to the optimal siting and sizing of the EV charging stations and renewable energy sources achieved by COA. The lower losses imply enhanced system performance, better utilization of distributed resources, and potential cost savings in distribution system operation.

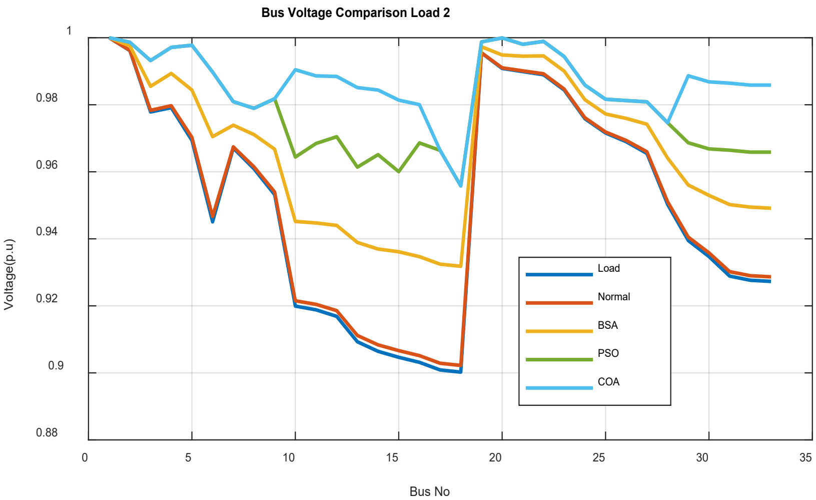

Figure 6. Bus Voltage Comparison of IEEE 33-bus system using different algorithms under Load 2.

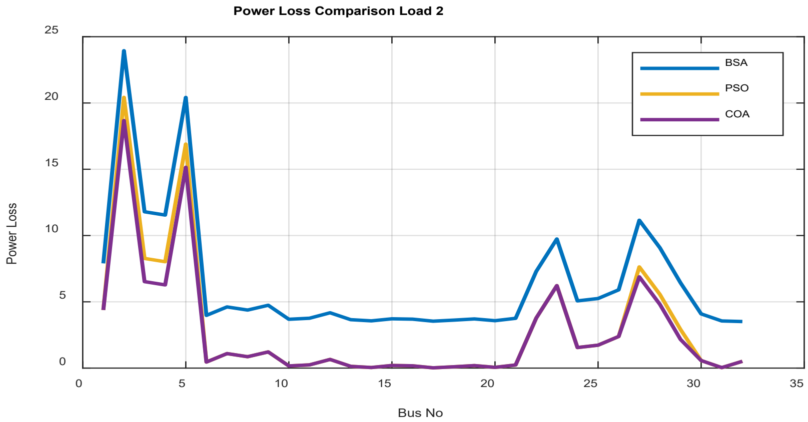

Figure 7. Power loss Comparison of IEEE 33-bus system using different algorithms under Load 2.

Fig 8 presents the bus voltage profiles under various load scenarios using different algorithms. It is observed that the Crayfish Optimization Algorithm (COA) consistently maintains higher and more stable voltages across the buses, regardless of the load condition. This demonstrates the robustness of COA in handling dynamic system loading, ensuring voltage levels remain within permissible limits. Fig 9 compares the total real power losses under different load scenarios for the same set of algorithms. The COA algorithm achieves the lowest power losses in all cases, indicating superior optimization of both location and capacity of EV charging stations and renewable sources. This reflects the efficiency and adaptability of the COA method in minimizing losses even as the load profile changes.

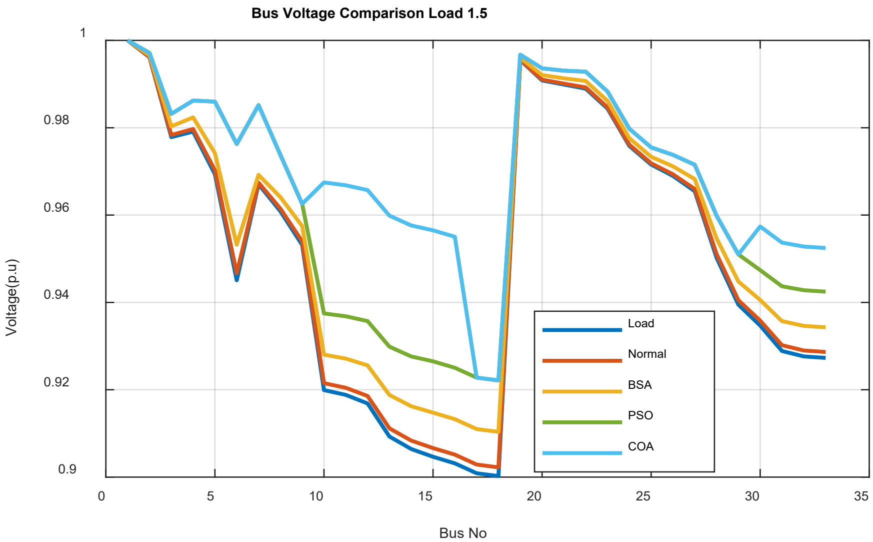

Figure 8. Bus Voltage Comparison of IEEE 33-bus system using different algorithms under Load 1.5

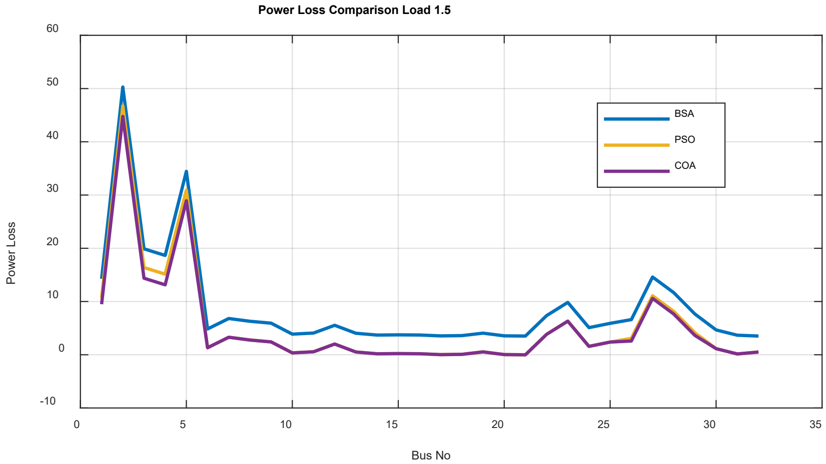

Figure 9. Power loss Comparison of IEEE 33-bus system using different algorithms under Load 1.5.

Figure 10 illustrates the voltage profile comparison of the IEEE 33-bus system before and after the integration of Renewable Energy Sources (RES). Before RES insertion, the voltage levels decrease progressively from the substation towards the remote buses, with some buses approaching or falling below acceptable limits due to line losses and load demand. After RES integration, the voltage profile shows significant improvement across the network as the locally injected power from RES reduces the load on feeder lines, minimizes voltage drops, and enhances overall voltage stability. This demonstrates that RES integration not only improves voltage regulation but also contributes to a more balanced and efficient power distribution system.

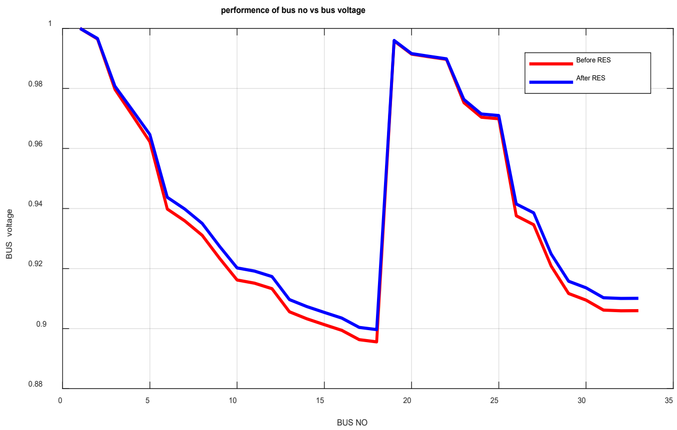

Figure 10. Voltage profile Comparison before and after RES insertion of IEEE 33-bus system

The simulation results in Table 1 clearly demonstrate that the proposed COA method outperforms both PSO and BSA in key performance areas. While PSO and BSA provide acceptable solutions, the COA achieves a lower power loss, more efficient allocation of renewable generation, and better siting of EV charging infrastructure. Notably, COA balances the use of solar and wind resources more effectively and minimizes losses by more than 10 kW compared to traditional methods. These findings justify the claim that COA is a more robust and effective optimization technique for integrated EV and renewable planning in distribution networks. COA and PSO both placed the EV charging station at Bus 15, indicating a strategic location that likely reduces line loading and improves voltage support in that part of the network. BSA chose Bus 9, which may not be as effective, possibly leading to less optimal power flow and higher loss compared to COA. COA places PV and wind at Buses 5 and 16, which are likely better distributed in terms of proximity to load centers or voltage-weak areas.In contrast, BSA's placement (Buses 4 & 29) and PSO's (Buses 20 & 7) may not yield the same system-wide impact. COA achieves the lowest total power loss: 196.54 kW, compared to:201.49 kW for BSA, and 207.19 kW for PSO.This means COA reduces losses by 5.29% compared to BSA and 10.3% by PSO respectively.

Table 1. Optimal Placement of RES under different algorithms

S.No	PSO	BSA	COA (proposed)
optimal Placement of Charging station at node no.	15	9	15
Capacity of Solar PV and wind mill (KW)	11 and 181	1 and 187	16 and 184
Optimal Placement of Solar PV and wind mill at node no.	20 and 7	4 and 29	5 and 16
Power Loss at load (KW)	207.19	201.49	196.54

5. Conclusion

This study proposes the ideal locations and dimensions for RES and EVCS inside a smart grid. The proposed method is COA. Reducing loss of power, voltage fluctuations, demand supply and charging costs, and EV battery prices is the main goal of the article. The optimization problem of RES and EVCS is solved with the help of the suggested method. The MATLAB platform is used to evaluate the proposed method and compare it with a number of other existing methods. In all methods that is currently in use, including BSA and PSO, the proposed approach performs better. Based on the outcome, it can be concluded that, in comparison to other methods now in use, the proposed approach's power loss and voltage fluctuations are minimal.

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