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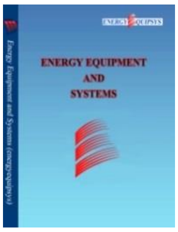

Optimizing EV charging station placement in power grids: A comparative study of PSO and GA for enhanced stability and reduced losses

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ABSTRACT

For the purpose of minimizing passive and receptive losses and giving the lowest possible voltage deviation, the IEEE standard 33-bus network is utilized in the current research to evaluate the capacity and position of EV charging stations. Therefore, according to their location, the current passing through the lines, the voltage of the phases, and, of course, the location of the loads, the voltage of the buses changes and can change the network expenses and the network voltage deviation profile. A charge is applied to the network since electric car owners show their likelihood of recharging based on a number of behavioral criteria, including the average charging time, the distance to the charging location, whether the charging location is busy or quiet, and other considerations. Therefore, this probabilistic behavior is dynamically modeled by queuing theory (modeled using Poisson's function), The uncertainty of other loads except for charging stations is modeled using the Monte Carlo distribution function, and finally, with the help of two cumulative algorithms, PSO and genetics, the ideal station placement is addressed, and the simulation's outcomes show appropriate operation. In terms of optimal positioning, particle algorithms outperform genetic algorithms.

Keywords: Charging Station, Electric Vehicle, Load Uncertainty, Microgrid, Optimal Location, Photovoltaic Unit, Queuing Theory.

1. Introduction

Due to their minimal carbon dioxide emissions and easy upkeep, electric automobiles are increasing in popularity more and more. However, as their numbers rise and the demand for charging grows, distribution networks face challenges such as power drops and high peak demand for charging at charging stations. This situation also affects consumer behavior. Consequently, a plan has been put up to lessen the energy strain on the network that considers the actions of investors, distribution network owners, users, and the utilization of green energy sources at CS. Additionally, an energy management strategy through battery charging and discharging and V2G has been implemented, along with the simulation of PV

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uncertainty using Monte Carlo methods Ahmad et al [1]. The energy storage system of electric vehicles is always faced with challenges such as overheating and low energy storage capacity. In order to combine the system's output flow and lower the energy storage system's volume and losses, the use of three-port bidirectional converters as an interface between the battery, supercapacitor, and electric motor has been proposed. Additionally, the direct control of power for both the battery and supercapacitor through the switching of these converters has been discussed Hatami et al [2]. EVCSs serve as the connection point between the transportation system and the electrical grid. The two networks are concurrently impacted by the way EVs operate. As a result, CS's ideal location inside a distribution network is quite important. A queuing model is used to analyze how the CS operates dynamically, helping to optimize its deployment while minimizing both network losses and the risk of EVs running out of charge on their way to the station. Sadhukhan et al [3], have used a PLM approach to account for unpredictability in electricity demand. Firoozmakan et al [4], to reduce costs and enhance microgrid reliability under the uncertainty of next-day operations, a stochastic energy management system is suggested. Both the islanded and grid-connected forms of microgrid operation are taken into account. The next generation of power networks is known as smart grids, where information and electricity flow both ways. Given the capability of electric vehicles to connect to the grid as either storage or consumption units, and their widespread use, their effects on voltage profiles and losses to the network are covered by Papadopoulos et al. [5]. On the other hand, as noted by Sadhukhan et al. [6], inappropriate CS placement may negatively affect urban traffic patterns and the distribution network. This study utilizes the standard IEEE 33-bus network and applies the NSGA-II algorithm to enhance CS utilization and minimize distribution network losses. In order to satisfy demand along the most likely routes, Fredriksson et al. [7] sought to determine the bare minimum of charging stations and their placements. Reddy et al. [8] optimized the radial distribution system using a heuristic method in an effort to reduce actual system losses by appropriate charging station location, since charging station placement raises system losses. Reddy et al [9] utilized a PSO algorithm for the optimal placement of CSs. Yang et al. [10] addressed the challenge of determining the appropriate size for fast charging stations, including the number of chargers and waiting spaces. They proposed an optimal planning approach grounded in the analysis of charging behavior over time. Arayici et al. [11] focused on the placement of CSs, considering factors such as accessibility and investment requirements.

To address the optimization problem, Ahmadian et al. [12] employed simulated annealing and Tabu search techniques to minimize operational costs in the network while adhering to technical constraints. The study demonstrated that both fixed battery units and DG are technically and economically necessary for the network.

Shekari et al. [13] applied the Cuckoo Search algorithm to analyze a 9-bus test system across three different scenarios. Their goal was to determine the optimal size and placement of parking facilities, considering that EVs can serve as both loads and energy storage units within the grid. In the meantime, Aghaebrahimi et al [14] used Monte Carlo simulation in addition to the Cuckoo optimization algorithm for optimization. A genetic algorithm and embedded Monte Carlo simulation were used by Shojaabadi et al [15] to solve optimization problems in both 9-bus and 33-bus networks. According to Liu and Hu et al [16], when taking battery longevity into account, using EVs in frequency control programs benefits EV owners more than peak reduction programs. The variation in daily energy demand from EVs has an economic impact on the power system Torreglosa et al [17]. Furthermore, Poullikkas et al. [18] looked at the early difficulties in using electric cars. Electricity plant dispatching involves balancing output and consumption, providing the necessary spinning reserve for a 24-hour period at the lowest cost, and determining the on/off status of units and the electricity they generate, Wang et al [19].

Power generating units' short-term planning has been managed by PSO in an effort to cut costs while accounting for grid-connected EVs. Reducing expenses and pollutants, Mozafar et al [20] and Pal et al [21] Awasthi et al. [22], Deb et al. [23], and Guo and Zhao [24], with an emphasis on reliability restrictions. To model the capacity available from these vehicles for providing ancillary services, a reliable probabilistic model must be developed for the vehicles present in multiple parking lots across different locations in the city, as well as at individuals' workplaces or homes. This can be seen as a group of CS lots that are handled as a single, sizable CS facility from the viewpoint of the local network operator. The number of cars in this enormous CS facility at any given time of day can be properly tracked by using neural networks to extract precise information. Hussein [25].

Recent studies have explored optimizing EVCS placement in power grids to enhance stability and reduce losses. Various optimization techniques have been employed, including hybrid Genetic Algorithm-Simulated Annealing, Kumar et al [26], Galaxy Gravity Optimization, Abdelaziz et al [27], PSO, Pal et al [28], and Spotted Hyena Optimizer Yuvaraj et al [29]. These methods aim to minimize power losses, voltage deviation, and improve system reliability. Integration of FACTS devices, such as Static Var Compensators and Thyristor-Controlled Series Capacitors, has been proposed to enhance stability Pal et al [28]. Additionally, combining distributed generation and distribution static compensators can mitigate EVCS impacts on radial distribution systems Yuvaraj et al [29]. Multi-objective optimization approaches considering both electrical and road constraints have been developed, Abdelaziz et al [27]. These studies demonstrate the importance of strategic EVCS placement in maintaining power grid stability and efficiency while accommodating the growing adoption of electric vehicles.

This study analyzes the IEEE 33-bus network to determine the optimal capacity and location of EVCSs to reduce voltage variation and passive and receptive losses. Due to their placement, these stations affect the voltage profile and network losses, which also influence the phase voltages and current flowing across the lines, which in turn impacts the voltage levels at the buses. Given that EV owners exhibit probabilistic behavior regarding charging based on their distance from the station, the congestion of the station, average charging time, and other factors, a load is applied to the network. This probabilistic behavior is dynamically modeled using queue theory, which is represented by a Poisson distribution. The uncertainty of other loads, apart from the charging stations, is modeled using a Monte Carlo distribution. Finally, the optimal location of the stations is addressed using two cumulative algorithms: PSO and GA. The PSO method outperforms the GA in terms of ideal position, according to simulation data.

The novelty of this work lies in its comprehensive approach to optimizing (EVCS) placement within the IEEE 33-bus network by integrating advanced methodologies. The key innovative aspects include:

- Dynamic Probabilistic Modeling: Utilizing queuing theory to dynamically capture the probabilistic behavior of electric vehicle owners, incorporating factors such as charging time, location distance, and congestion, for a realistic user behavior representation.
- Monte Carlo Simulations for Load Uncertainty: Employing Monte Carlo simulations to account for variable load uncertainties, ensuring robust network performance analysis and reliable optimization results.
- Algorithmic Comparative Analysis: Conducting a comparative evaluation of Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), highlighting PSO's superior performance in EVCS placement.
- Focus on Voltage Stability and Loss Minimization: Addressing critical challenges by optimizing EVCS placement while minimizing passive/reactive losses and maintaining voltage stability.
- Practical Real-World Application: Demonstrating applicability through the IEEE 33-bus network, providing actionable insights for policymakers and industry stakeholders.
- Integrated Framework: Combining queuing theory, Monte Carlo methods, and optimization algorithms into a scalable, adaptable framework for EV charging infrastructure planning.

This integrated approach ensures the study's relevance and applicability to real-world challenges in energy management and EV infrastructure development.

This paper's structure is as follows: The broad framework in Section 1 is established by the problem description, which also specifies the goal function and limitations. In Section 2, the problem model is formulated. While findings and conclusions are presented in Section 4, network information and simulation results are presented in Section 3.

Nomenclature

BSS	Battery Storage System
V2G	Vehicle to Grid
GA	Genetic Algorithm
PEVs	Plug-in Electric Vehicles
PSO	Particle Swarm Optimization
PLM	Probabilistic Load Modelling
TH	Thermal Heat
PEMFC-CHP	Proton Exchange Membrane Fuel Cell- Combined Heat and Power
CS	Charging Station
PV	Photo Voltaic
FA	Firefly Algorithm
EVCS	Electric Vehicle Charging Station
EMCS	Energy Management and Control Systems
GWO	Grey Wolf Optimization
EV	Electric Vehicle
AHP	Analytical Hierarchy Process
V2G	Vehicles to Grid
DG	Distributed Generation
PDF	Probability Density Function
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
WT	Wind Turbine
PV	Photo Voltaic
ELM	Extreme Learning Machine
DER	Distributed Energy Resource
WT	Wind Turbines
PV	Photo Voltaic
V2G	Vehicle-to-Grid
FACTS	Flexible AC Transmission System

2.State the problem

As will be covered in more detail below, the specification of the objective function and the associated restrictions serve as the foundation for reducing voltage fluctuation and minimizing both passive and receptive losses. Furthermore, Figure 1 shows how the simulation is conducted in the study of optimizing the placement of EVCS.

2.1 Utilizing Queueing Theory to Assess the Capacity and Load Distribution of EVCS

This section describes a technique that uses user equilibrium, M/M/s queueing theory, and Yao et al. [30] to simulate the size and load profile of EV quick CSs. According to Yao et al [30], the traffic allocation problem is initially resolved using user equilibrium to determine the pace at which cars arrive at the CS. Using queueing theory, the next step calculates the fast CS's capacity based on the number of vehicles requesting charging and their maximum wait time in line. In accordance with queueing theory and Markov theory, a mathematical model for the fast charging station's demand is finally presented by Bae and Kwasinski [31].

2.2. Mechanism for Allocating Traffic Using Consumer Equilibrium

One popular model for traffic modeling in cities is the User Equilibrium (UE) traffic allocation model. According to Xiang et al [32], this model assumes that drivers automatically try to maximize their travel time by taking the quickest and most cost-effective route, which has an impact on how the power system operates, as stated by He et al [33].

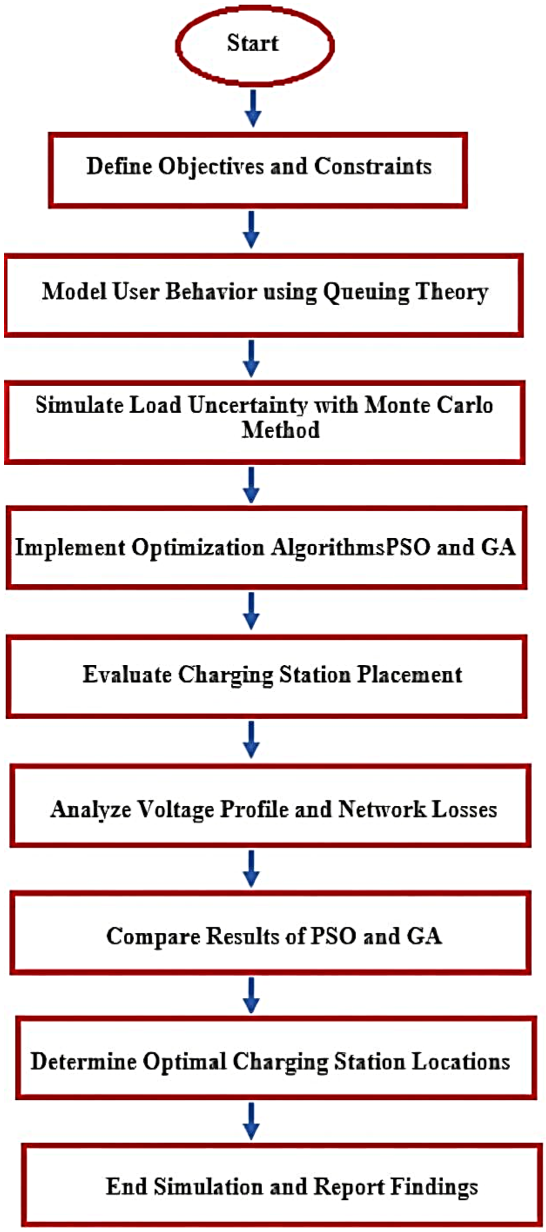

Fig. 1. Flowchart for Simulation Process.

To model traffic using the UE model, various algorithms can be employed, such as the Frank-Wolfe algorithm, the external effects algorithm, and the simultaneous algorithm. These algorithms aim to find the equilibrium traffic that creates the best distribution of drivers across different routes in the city. Based on the results obtained from the UE model in the traffic network $G(N^T, \Omega^{TL})$, where N^T represents traffic nodes and Ω^{TL} represents traffic arcs, traffic can be controlled in areas with the highest demand, allowing for the establishment of CSs in those regions. Yudai et al [36] formulate the UE problem with the goal of volume on arcs at each interval as

$$min f_x = \sum_{(mn)\in\Omega^{TL}} \int_0^{x_{mn}} p_{mn}(\omega)d\omega \,. \tag{1}$$

In the above relationship, $p_{mn}(\omega)$ is the Travel time-arc volume function mn. Some of the constraints that make up the suggested optimization problem are given by

$$\sum_{q\in Q_{rs}} f_q^{rs} = q_{rs} \tag{2}$$

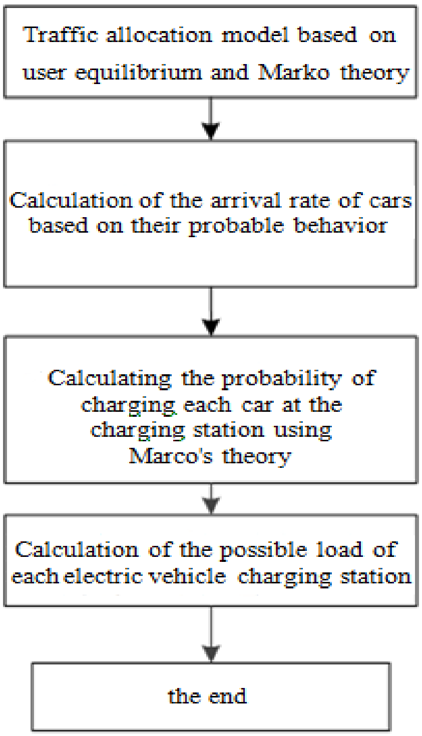

Fig. 2. Examining the steps involved in figuring out an EVCS's capacity and power demand Timouri [34].

$$f_q^{rs} \geq 0 \tag{3}$$

$$x_{mn} = \sum_{r\in N^T}\sum_{s\in N^T}\sum_{q\in Q_{rs}} f_q^{rs}\delta_{mn,q}^{rs} \tag{4}$$

In this context, f_q^{rs} represents the traffic volume or flow on path q between origin r and destination s, while q_{rs} indicates the travel demand between origin r and destination s. X_{mn} is the traffic volume on path mn, and $\delta_{mn,q}^{rs}$ is a binary variable, taking a value of 1 if arc mn is part of path q between origin r and destination s, and 0 otherwise. Q_{rs} denotes the set of all possible routes between origin r and destination s. Eq. (2) guarantees the conservation of flow within the network, meaning the total flow across all paths between each origin-destination (O-D) pair is equal to the travel demand for that specific O-D pair. Equation (3) establishes a non-negativity constraint on the traffic flow for path q between origin r and destination s, while Eq.(4) defines the relationship where the flow on arc is the sum of the flows across all paths that include arc mn. Farkas and Szűcs and Prikler [37], Aimsun, a micro and macro simulation software, was used to solve the User Equilibrium (UE). If we represent $f_{k,t}$ as the traffic flow handled by the K_{th} CS at time t, then $f_{k,t}$ can be determined based on the traffic allocation results at time t, as outlined in

$$f_{k,t} = \sum_{r\in N^T}\sum_{s\in N^T}\sum_{q\in Q_{rs}} f_{q,s}^{rs}\delta_{k,q}^{rs}\, u_k \tag{5}$$

(Aghapour et al. [35]). In the equation above, $\delta_{k,q}^{rs}$ is a binary variable (representing the traffic flow between the origin-destination pair rs managed by charging station, k), and U_k is the decision variable that determines whether a CS is built or not. In other words, U_k indicates the number of vehicles that have passed through traffic node k.

2.3.Using Queue Theory and Markov Chains to Model the Capacity of EV Fast CS

With this approach, a Markov chain can be used to determine the likelihood that an EV can be charged at a fast charging stationIn this case, the probabilistic Markov model considered for charging the batteries of electric vehicles [36]. The following is a description of this strategy's numerical simulation: The maximum quantity of batteries for electric vehicles is denoted by N. Therefore, equations

$$P_N = \frac{\frac{(c\rho)^N}{(N)!}}{\sum_{i=0}^{c} \frac{1}{i!} (\frac{\lambda}{\mu})^i + \sum_{j=c+1}^{N} \frac{1}{c^{j-c}} \frac{1}{c!} (\frac{\lambda}{\mu})^i} : N < c \quad (6)$$

$$P_N = \frac{\frac{(c\rho)^c}{(c)!} (N - c)}{\sum_{i=0}^{c} \frac{1}{i!} (\frac{\lambda}{\mu})^i + \sum_{j=c+1}^{N} \frac{1}{c^{j-c}} \frac{1}{c!} (\frac{\lambda}{\mu})^i} : N < c \quad (7)$$

can be used to define the chance of EV charging if some batteries (those that are currently being charged) are represented by N, Farkas and Szűcs and Prikler [37]. In the above relations, P_N is the probability factor of electrical usage at a fast EVCS in the relationships above. λ is the percentage of success of a car in using the charging converter, μ is the achievement pace of a car finishing its battery charge, and $\rho = \frac{\lambda}{c\mu}$: the traffic intensity rate, where c is a count of charging devices available for EVs.

3. Developing the Goal Function Formula

3.1. Function Formula of Loss

The transmission capacity of lines in electricity networks is constrained by inherent losses, which also place a heavy burden on the network. Designers aim to calculate these losses using the Newton-Raphson load flow method and consider them as a critical factor in the objective function equation. In this context, power losses (MVA) in the transmission line are calculated using

$$Total\ Losses(MVA) = \sum_{k=1}^{NL} S_{L_{ij}} = \sum_{k=1}^{NL} (S_{ij} + S_{ji}) \quad (8)$$

where $S_{L_{ij}}$ is the losses in the wiring path across buses i and bus j, S_{ij}: complex power passing from bus i to bus j, and S_{ji} this is the inverse of S_{ij}. Furthermore, the network's transmission line count is indicated by NL. These quantities are calculated as

$$S_{ij} = V_i I_{ij}^* \quad (9)$$

$$S_{ij} = V_j I_{ji}^* \quad (10)$$

where I_{ij} represents the complex current flowing through the transmission line connecting bus i to bus j, V_i represents the complex voltage at bus i, and V_j represents the complex voltage at bus j.

3.2. Voltage deviation function

When choosing the best capacity and location for electric vehicle parking, this paper also aims to minimize voltage deviation in the power network. The voltage deviation amount is determined using

$$VD = \sqrt{\sum_{i=1}^{Nb} \left(\frac{V_{standard}}{V_{Base}} - \frac{V_i}{V_{Base}}\right)^2} \quad (11)$$

3.3. Constraints of the Problem

To maximize the intended goal function, the following constraints must be considered. By changing the maneuver points of the distribution network, a new configuration is created. However, it cannot be said that every newly found configuration is always suitable. As a result, the network configuration that emerges from every modification needs to follow these guidelines: Relation (13) displays the allowable current flow through the lines, while Relation (12) displays the allowable voltage range at the nodes. However, the network's continued radiality after placement is the primary limitation in the location problem within a radial network. The network's radial structure ensures that no node in the network is left without power and that no loops are formed. Two straightforward computations are employed in order to meet this constraint. That is

$$V_{min} \le V_i \le V_{max} \quad (12)$$

$$I_{min} \le I_i \le I_{max} \quad (13)$$

The first computation (a prerequisite) requires that the network circuit's line count be one fewer than its bus count. After assessing the first calculation, the determinant of the branch-node incidence matrix is used to complete the second calculation (sufficient condition) to avoid bus isolation, as indicated by

$$\det(A) = 1\ or - 1 \quad (14)$$

$$\det(A) = 0\,. \quad (15)$$

Increasing the electricity passing through the transmission lines boosts their temperature since power lines have a limited thermal capacity. As a result, the power flow constraint on the transmission lines, defined by

$$P_{T.i}^{min} \leq P_{T.i} \leq P_{T.i}^{Max} \quad (16)$$

is one of the key factors that must be considered to address the current problem effectively.

3.4. An explanation of the system's objective function

In contrast to traditional optimization issues, which usually yield a single optimal solution, the optimization model presented in this study is constructed as a multi-objective problem, containing numerous conflicting objectives. Within this framework, the decision-maker can select a preferred solution from the set of points on the Pareto front, as any solution meeting the defined constraints is considered optimal. To achieve the goals of optimal and secure energy placement and management within the given constraints, it is essential to collect a variety of data. This information must be calculated for every hour of the preceding day and comprises unit scheduling, the generation capacity of every controlled DG unit, and power transactions with the main grid.

The main objective of this thorough planning approach is to guarantee the network's safe and efficient functioning while taking into account all pertinent technological factors. An optimizing multiple goals formulation centered on the GWO algorithm is used to tackle the problem in order to achieve this. The balancing and optimization of several objectives linked to network energy management and operation is dealt with using

$$min\{F_i(P_{DG_i}.S_i)\} \quad (17)$$

which defines the planning issue with a multi-objective function. In Eq. (17), Fi stands for the goal functions specified in the placement problem in the equation above, which are dependent on the independent variables P_{DG_i} (capacity of DG) and L_{DG_i} (location of distributed generation resources). Consequently, the following formulation of the goal's functions in this situation is possible:

$$F_1(P_{DG_i}.L_{DG_i}) = Total\ Cost = \underbrace{C_{PV}(P_{PV})}_{PV\ Cost} + \underbrace{C_{wt}(P_{wt})}_{wind\ turbine\ cost} + \underbrace{C_{MT}(P_{MT})}_{microturbine\ cost} + \underbrace{C_{Dg}(P_{Dg})}_{Deiel\ cost} + \underbrace{C_{utility}(P_{utility})}_{utility\ cost} + \underbrace{C_{DR}(P_{DR})}_{Demand\ Response\ cost} + \underbrace{C_{EV}(P_{EV})}_{EV\ Cost} \quad (18)$$

$$F_2(P_{DG_i}.L_{DG_i}) = Losses = \sum_{k=1}^{NL} S_{L_{ij}} \quad (19)$$

$$F_3(P_{DG_i}.L_{DG_i}) = Voltage\ Deviation = \sqrt{\sum_{i=1}^{Nb}\left(\frac{V_{standard}}{V_{Base}} - \frac{V_i}{V_{Base}}\right)^2} \quad (20)$$

$$F_4(P_{DG_i}.L_{DG_i}) = Load\ ability\ Limit \quad (21)$$

$$F_4(P_{DG_i}.L_{DG_i}) = (1 - \sum_{k=1}^{nb}\frac{I_k^*(F)}{I_k(F)})) \quad (22)$$

$$F_6(P_{DG_i}.L_{DG_i}) = EENS \quad (23)$$

In a distribution network that integrates various generation and consumption resources as well as connected microgrids, there is always the potential for bidirectional energy exchange between the grid, microgrids, and other energy resources. In order to optimize overall advantages, this system balances various objectives while every goal's function aims to accomplish its own specialized goals. Thus, taking into account the different ways that microgrids can operate, the multiple goal functions that represent the network's overall management of energy program are mathematically constructed as follows. The formulation given by

$$min\{OF_{Total}\} = [\chi_{12} \quad \chi_{12} \cdots \quad \chi_{pk}] \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_k \end{bmatrix}. \quad (24)$$

aims to optimize energy flows and system performance while ensuring the safety, reliability, and efficiency of all network components. In Eq. (2) χ_{pk} is the weighting factor for the objective functions presented in

Eqs. (18) to (23). All events and system attributes must be considered when assigning weighting coefficients to the objective function. These factors include the system's operational status during repair or replacement, the time required for replacement, and the probability of failure of various system components. Additionally, fault events must be taken into account based on their duration and location in the system, as each introduces different operating conditions. The weighting coefficients are adjusted accordingly to reflect these factors and ensure that the optimization process accurately represents the system's behavior under various failure and recovery conditions. This method makes it possible to optimize the system more precisely and effectively, which raises its overall dependability and effectiveness.

3.5. GWO Algorithm-Based Encoding

In order to use the algorithm known as GWO for computations, the goal equation's variables have to be encoded. In this study, two key parameters—installation placement and capacity of EVCSs are encoded. Each parameter is represented by a number or "wolf" in a single dimension. The first number corresponds to the location of the distributed generation source, while the second number indicates the distance of each wolf to the target, which determines the capacity of the distributed generation resources. The problem is then formulated based on Eq.(24). Table 1 provides an example of encoded locations for charging stations, illustrating how the algorithm encodes these locations and integrates them into the optimization process. In the GWO algorithm, the Alpha represents the best available solution, while the Beta and Delta correspond to the second and third best solutions, respectively. The remaining solutions are classified as Omega. The Alpha and Delta wolves in this algorithm dominate the hunting process, while the remaining wolves follow these three leaders. The attack begins when the Alpha wolf leads the pack, and the prey is encircled by the wolves and unable to flee.

The reduction vector an is utilized to model this operation. The vector a in this model is given a value at random from $[-2a, 2a]$. As a decreases, the coefficients of vector A also decrease. The Alpha wolf and other wolves approach the prey more closely if |A|<1, while they move away from the prey if |A|>1. In the GWO algorithm, all wolves adjust their positions based on the positions of the Alpha, Beta, and Delta wolves. This iterative process continues until the optimal point, representing the prey's position, is reached.

3.5.1. Surrounding the Prey by GWO

Grey wolves encircle their victim while hunting. The behavior of the wolves during this surrounding process is represented through a mathematical model given by

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right| , \qquad (25)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} . \qquad (26)$$

In these equations, t represents the current iteration, A and C are coefficient vectors, Xp denotes the position of the prey, and X indicates the position of the wolf. The GWO algorithm computes vectors A and C in this order:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} . \qquad (27)$$

$$\vec{C} = 2.\vec{r}_2 . \qquad (28)$$

Table 1. Encoded dimension for the Gray Wolf algorithm

	Location (Bus number)	nominal values (KVA)
EVCS (1)	3	600
EVCS (2)	21	800
EVCS (3)	12	700
EVCS (4)	14	500

Although r_1 and r_2 are vectors that are randomly generated between a range of [0, 1], the parameter $\vec{A}$ in the aforementioned equations declines linearly from 2 to 0 over the algorithm's repetitions. The Alpha wolf usually takes the lead in the hunting effort; however, the Beta and Delta wolves may occasionally assist. According to the mathematics theory of grey wolf action while hunting, Alpha, Beta, and Delta wolves are said to have superior awareness of the possible locations of the prey. Hence,

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|. \quad \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|. \quad \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right|. \tag{29}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\left(\vec{D}_\alpha\right). \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\left(\vec{D}_\beta\right). \quad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\left(\vec{D}_\delta\right). \tag{30}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3} . \tag{31}$$

3.5.2. Search Stage

The hunting and search phases of the process are completely different. When |A|>1, the wolves separate from one another to pursue the prey. In contrast, they approach one another during the attack phase (when |A|<1) after tracking the prey. Common terms for the method of diverging during the search and convergence during the attack are "exploration-divergence" and "exploitation-convergence."

- Exploration: When |A|>1, the wolves distance themselves from the prey and search the space more effectively to locate it.
- Exploitation: The wolves approach the prey and use the information they have obtained to improve the solution when |A|<1.

The role of the vector C: The vector C represents natural obstacles that prevent wolves from rapidly approaching the prey. This vector is weighted toward the prey and makes it more challenging for the wolves to reach it. Unlike the vector a, C does not decrease linearly from 2 to 0; instead, it remains constant within the range of 2 to 0, maintaining its influence throughout the optimization process.

3.5.3. Algorithm Process

All potential solutions are computed at the start of the procedure, and the top three are chosen to be the Alpha, Beta, and Delta wolves. Throughout the program, these choices are kept constant. The prey's position is estimated by the three best solutions (Alpha, Beta, and Delta) utilizing optimization equations in each iteration.
The different answers (Omega wolves) adjust their places dependent on the Alpha, Beta, and Delta wolves' positions after each iteration.
The vector a (and so A and C) is modified in every iteration.
The position of the Alpha wolf is identified as the ultimate ideal spot at the conclusion of the iterations.

3.5.4. Optimization Process Flowchart

Figure 3 illustrates the flowchart of the optimization process, depicting the overall execution of the Grey Wolf Optimization algorithm. This flowchart includes various steps, such as calculating and updating positions and monitoring stopping conditions to reach the optimal point.

4.The outcomes of the simulations

4.1.Data input for the case study

The standard IEEE 33-bus power test network is used, as illustrated in Fig.3, to test and validate the suggested approach for determining the capacity and best location of EVCSs while taking uncertainties into account. Before and after the charging stations are installed, the network's modeling results are examined and contrasted.
In this study, DERs such as WT, PV systems, microturbines, diesel generators, and energy storage systems are integrated into the network under analysis. To model the uncertainties associated with load demand, solar irradiance, temperature, and wind speed, the Monte Carlo method is employed.

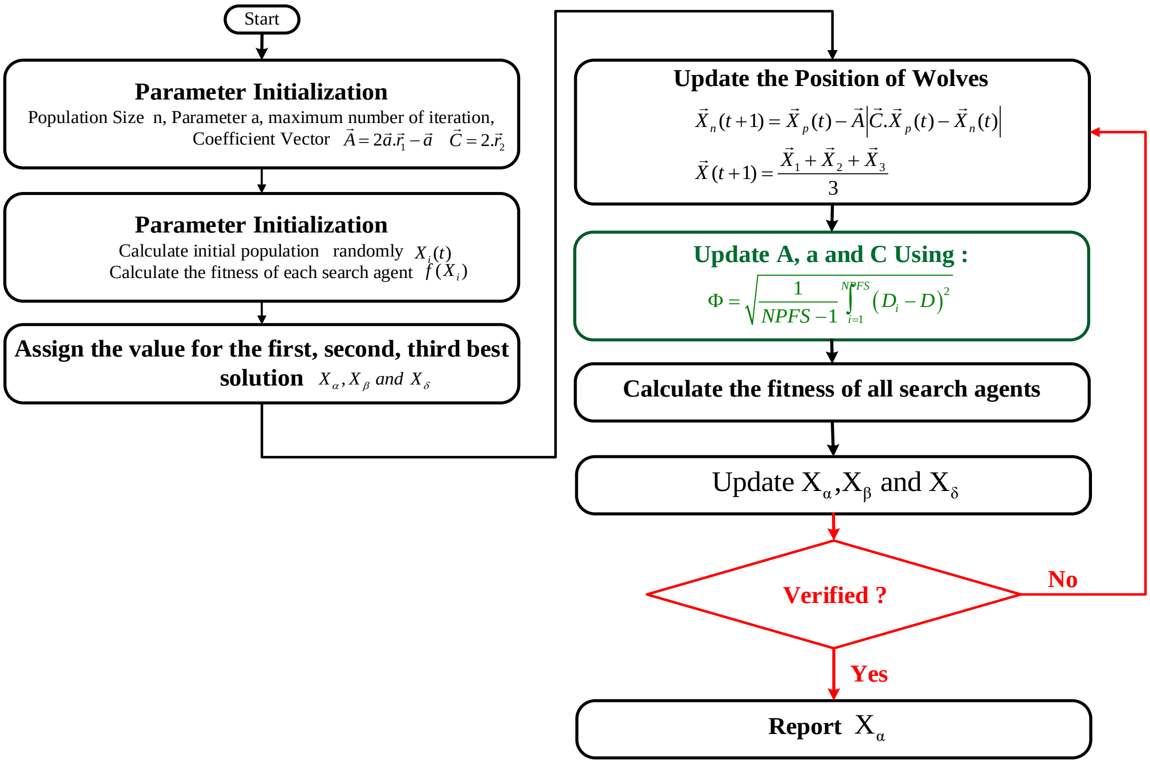

Fig. 3. Flowchart of the Gray Wolf algorithm optimization process.

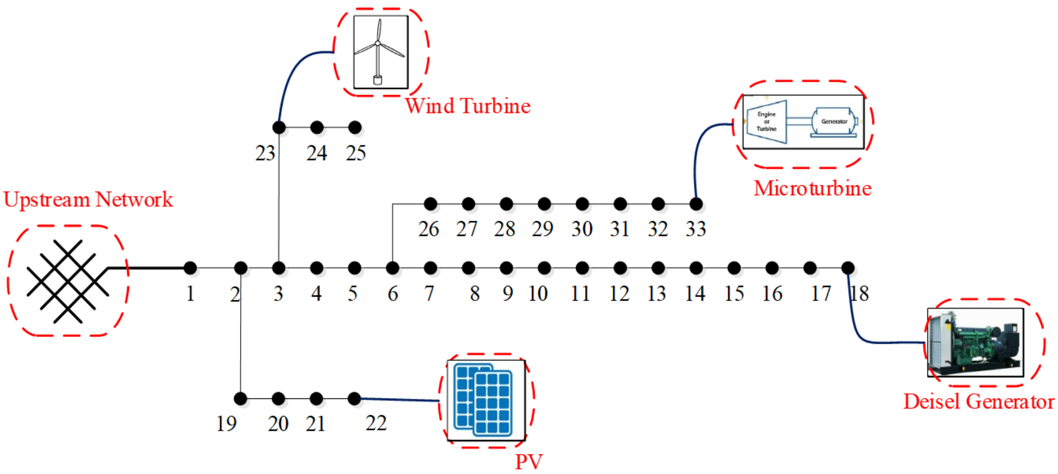

Fig. 4. Schematic of a standard IEEE 33-bus.

In this context, the PDF for the load points is illustrated in both 3D and 2D graphs in Fig. 5. As observed in Figs. 5.a and 5.b, the load points at each bus do not have a fixed value; instead, the load values at each bus are represented as ranges with varying probabilities of occurrence. This variability results in random load values during each iteration of the Monte Carlo simulation based on the shown probability density functions. Additionally, the load variation coefficient for each hour of the 24-hour daily cycle is depicted in Fig.6.

Furthermore, the PDF of wind speed for the wind power plant and the data for solar irradiance and ambient temperature for the photovoltaic plant at the studied site are presented in Figs. 6 through 8, respectively.

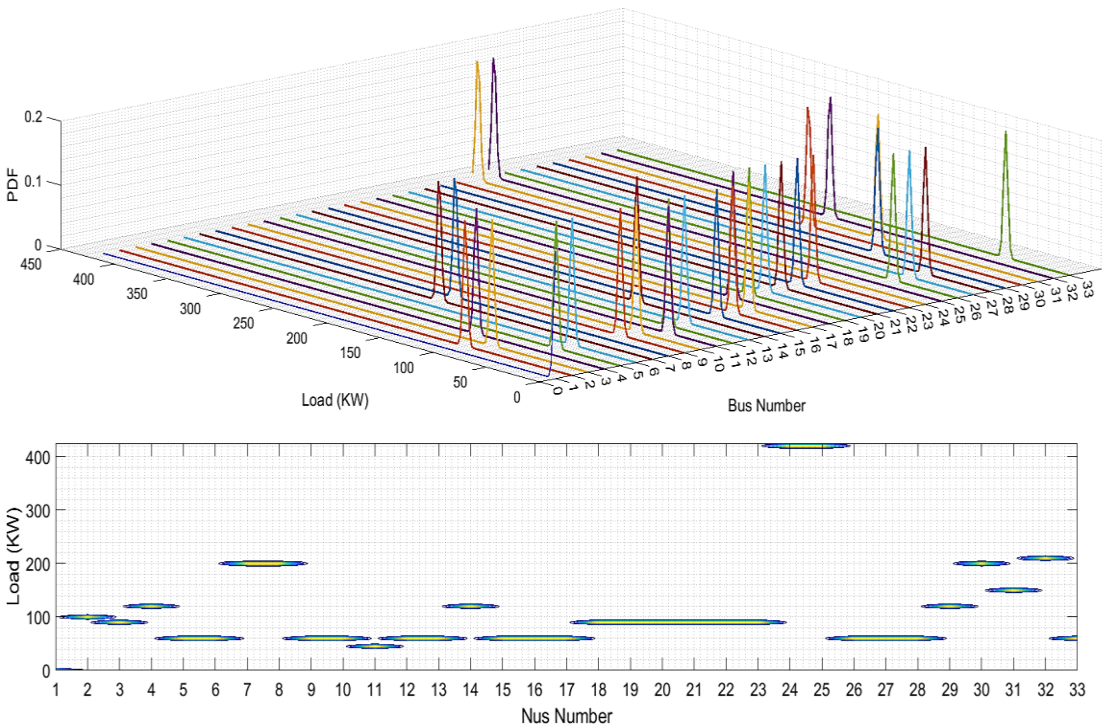

Fig. 5. PDF of load points in 3D and 2D (planar) representations for the 33-bus network.

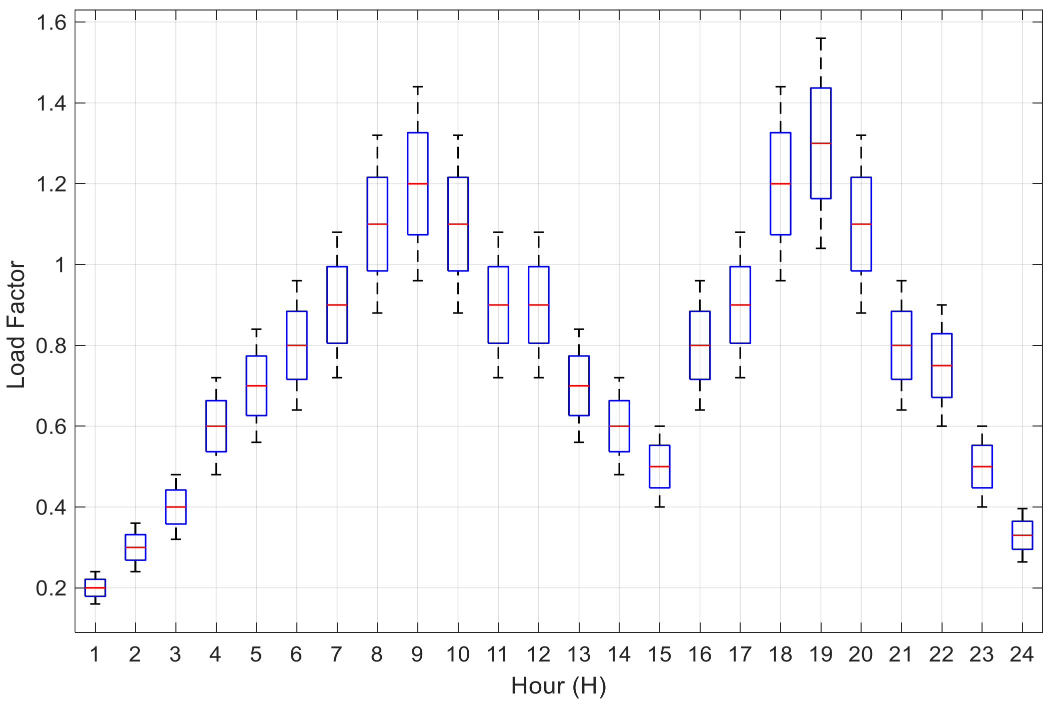

Fig. 6. Display of load factor changes 24 hours a day.

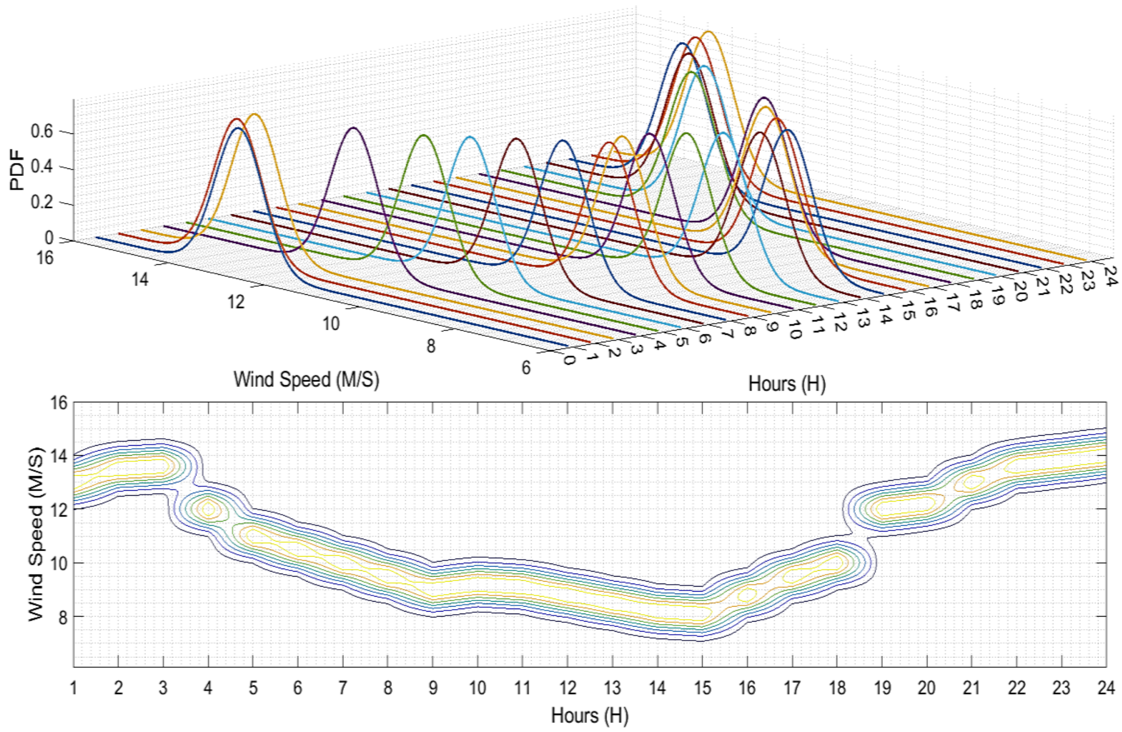

Fig. 7. PDF of wind changes over 24 hours a day.

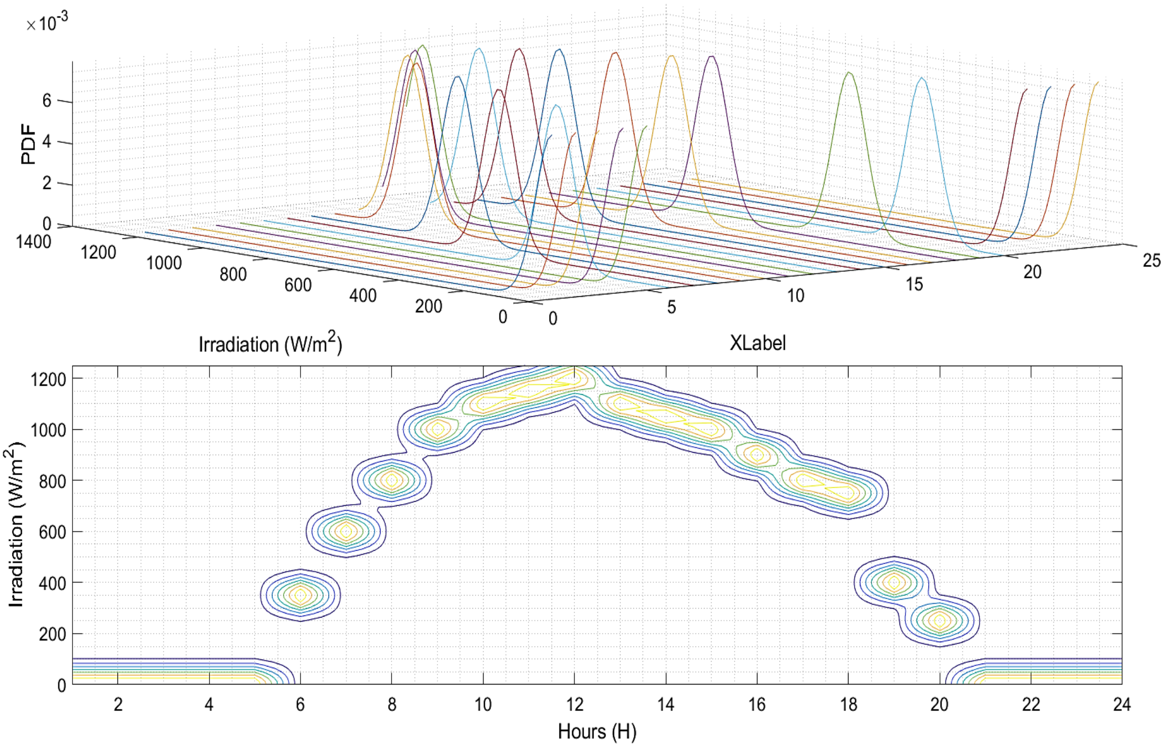

Fig. 8. PDF of solar radiation changes over 24 hours a day.

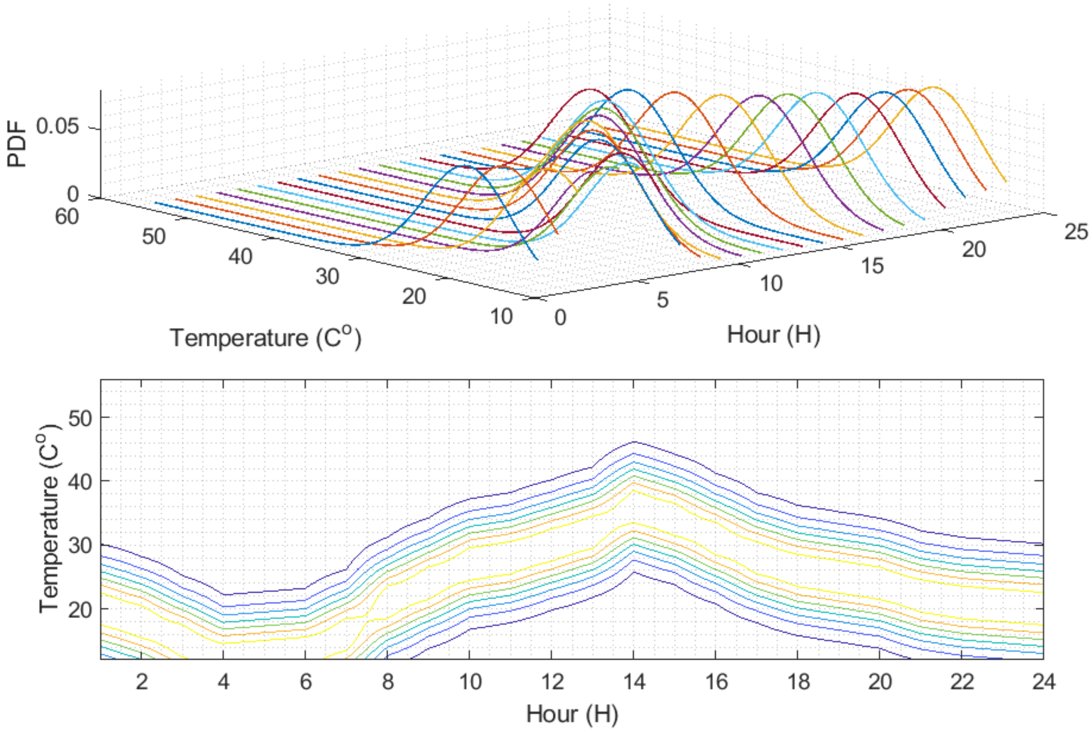

Fig. 9. PDF of ambient temperature changes over 24 hours a day.

4.1.1. Cost function of photovoltaic systems and temperature and radiation profiles

In this section, Eq. (30) specifies the cost function of the PV system to optimize the objective function given by

$$C_{PV} = 29.55 + 1.15P_{PV} \ . \tag{32}$$

Breakdown of Elements:

1. C_{PV}:

- This represents the total cost associated with the PV system. It could encompass initial capital costs, operational and maintenance costs, or other economic factors that contribute to the overall expenditure related to the PV system.

2. P_{PV}:

- This indicates the PV system's power output, which is commonly expressed in megawatts (MW) or kilowatts (kW). It shows how much electricity the solar panels are producing at any particular moment.

3. Constant Term (29.55):

- This is a fixed cost component that may represent baseline expenses such as installation, fixed operational costs, or other costs that do not vary with the PV system's power output. It indicates that there are inherent costs associated with having the system in place, regardless of how much power it generates.

4. Coefficient (1.15):

- The PV system's variable cost per unit of power is indicated by this coefficient. In this case, it suggests that for every additional unit of power output (e.g., kW or MW), there is an additional cost of 1.15 units (e.g., dollars) associated with that power generation. This could reflect costs related to maintenance, wear and tear, or other operational expenses that increase as power production rises.

4.1.2. The wind profile and turbine cost function

Similarly,

$$P_{wt}(\nu) = \begin{cases} 0 & if \nu < 8 \\ P_R(0.2 + 0.02\nu + 0.003\nu^2) & if\ 8 < \nu < \\ P_R & if\ 12 < \nu < \\ 0 & if\ 4 < \nu \end{cases} \tag{33}$$

$$\mathrm{C_{wt}(P_{wt}) = 85 + 1.05P_{wt}} \tag{34}$$

4.1.3.The microturbine and diesel generator's cost function

The price function of the diesel generator and microturbine, taking emission costs into account for the purpose of optimizing the objective function are defined by

$$C_{dg} = \left(431 + 6.53P_{dg} + 1.04^{-4}\right) + CF_{Dg,t}^{EMI} , \quad (35)$$

$$CF_{Dg,t}^{EMI} = \left(C_{co_2} \times Co_2 + C_{so_2} \times So_2 + C_{No_x} \times NO_{x_{DG}}\right) \times P_{Dg} , \quad (36)$$

where

$C_{co_2} = 1.24$.
$C_{so_2} = 2.41$.
$C_{No_2} = 1.28$.

In addition, in this context, the emission cost functions for both sources of generation are defined by

$$C_{mt} = \left(551.21 + 4.26P_{dg} + 0.94^{-4}\right) + CF_{mt,t}^{EMI} \quad (37)$$

$$CF_{mt,t}^{EMI} = \left(C_{co_2} \times Co_2 + C_{so_2} \times So_2 + C_{No_x} \times NO_{x_{DG}}\right) \times P_{mt} \quad (38)$$

where

$C_{co_2} = 1.24$
$C_{so_2} = 2.41$
$C_{No_2} = 1.28$

4.1.4.Grid-based electricity purchase tariff

A part of the total price function in this paper defines the price function for the power purchase tariff from the grid and is given by

$$C_{Utility} = 100 + 8.1 \times P_{utility} . \quad (39)$$

The objective function introduced in Eq. (24) is optimized using the GWO algorithm within a Monte Carlo iteration loop, which models the uncertainties of generation and consumption, in order to implement the suggested optimal placement model taking uncertainties into account.

4.2. Review and analysis of simulation results

Figures 10 to 13 display the charging stations' ideal location and capacity following the implementation of the optimal placement program. With the most optimal capacity of 500 kW, bus number 30 has the largest probability density for the ideal placement of the first CS, as illustrated in Fig.10. In the meantime, bus number 12 has the maximum optimal capacity of 500 kW and the largest probability density for the second charging station's ideal position, as shown in Fig.11. Likewise, as illustrated in Figs. 10 and 13, buses 30 and 2 have 500 kW and 500 kW capacities, respectively, making them the best locations and capacities for CSs 3 and 4.

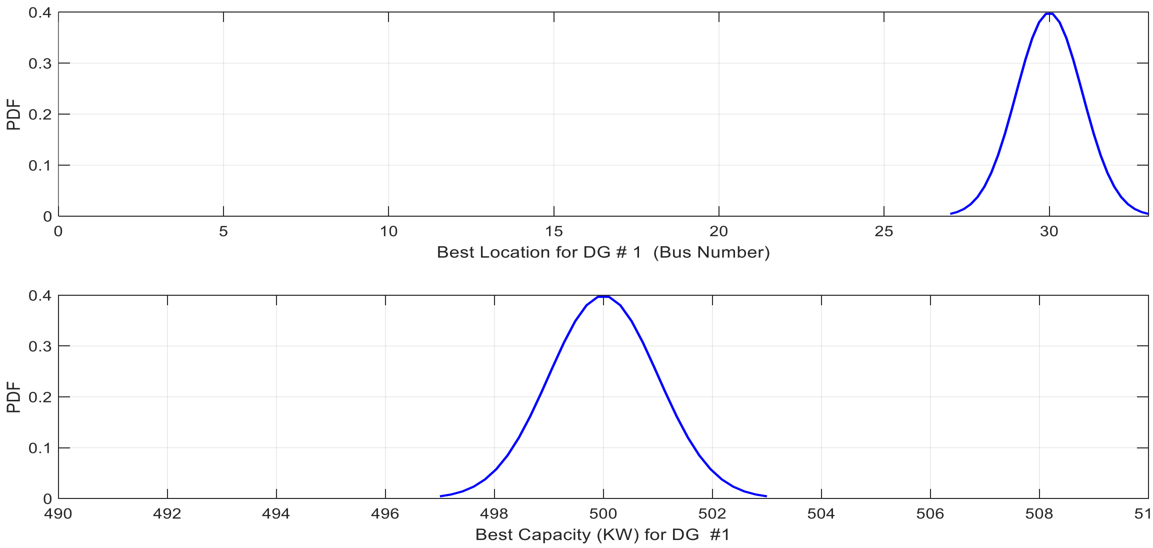

Fig. 10. PDF of optimal location and capacity of CS number (1).

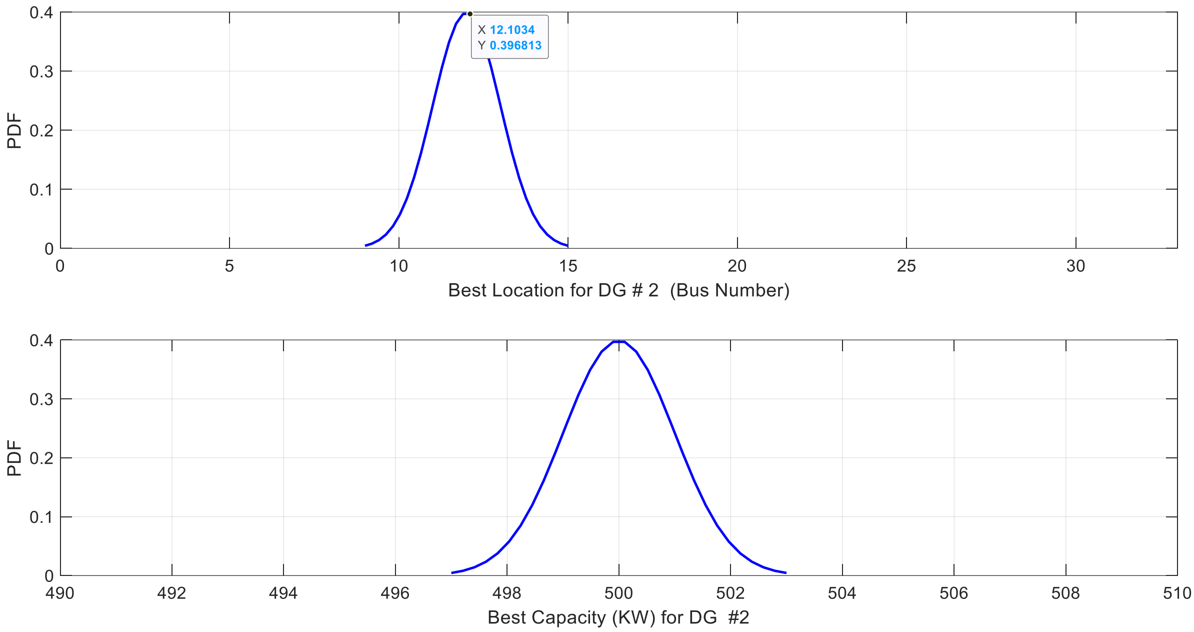

Fig. 11. PDF of optimal location and capacity of CS number (2).

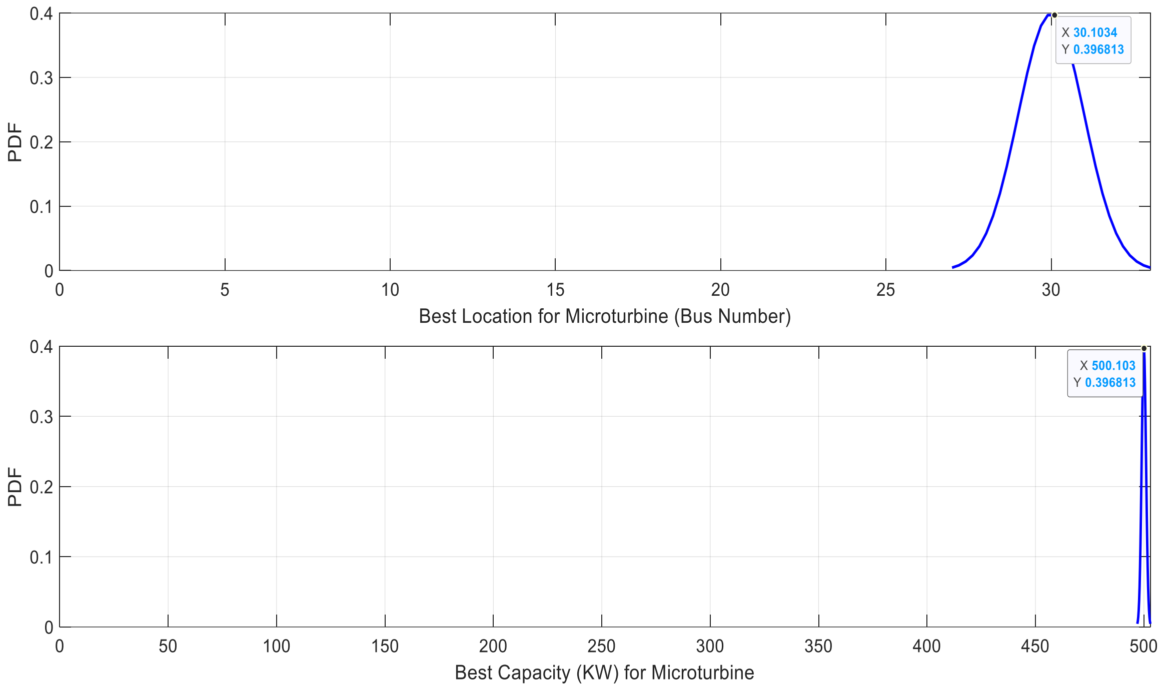

Fig. 12. PDF of optimal location and capacity of CS number (3).

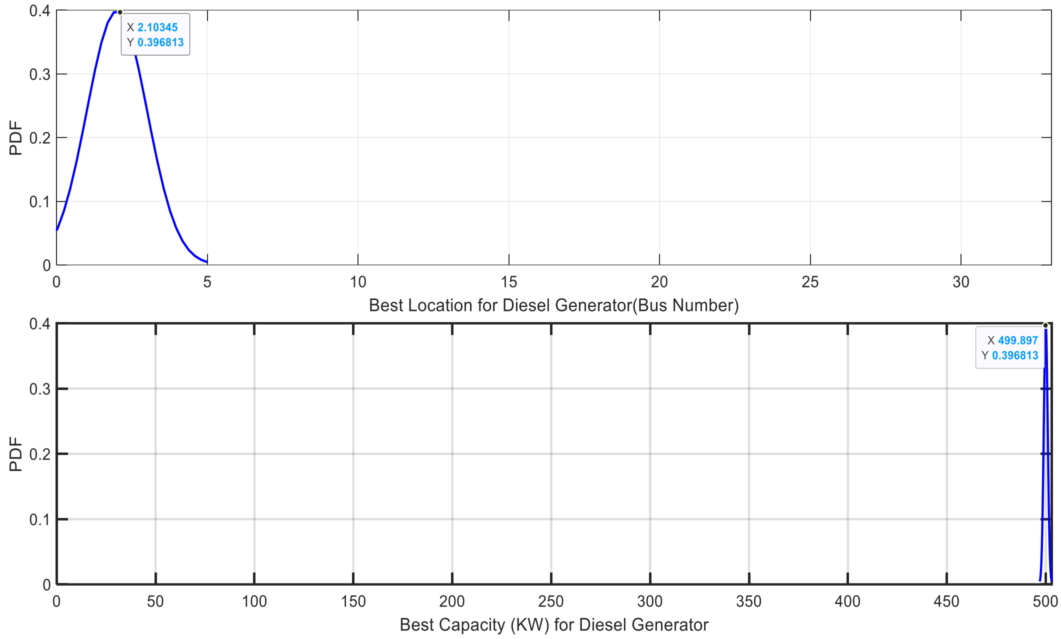

Fig. 13. PDF of optimal location and capacity of CS number (4).

The cost function graphs of the production units in both before and after the placement scenarios appear in Fig.15. As seen in this figure, the highest probability density value of the production costs in the post-placement scenario is significantly lower than the production costs in the pre-placement scenario. As observed in this figure, even in points with very low probability density, the production cost values in the post-placement scenario are much lower than the total production costs in the pre-placement scenario.

On the other hand, in Fig.14, the chart of the total 24-hour losses for both before and after the optimal placement scenarios is shown. Similar to the previous case, in this scenario, the losses in the most restrictive case (losses with the lowest probability density) after the placement are significantly lower than the losses in the pre-placement scenario. Figure 15 illustrates how this trend is replicated for the network's 24-hour voltage deviation index.

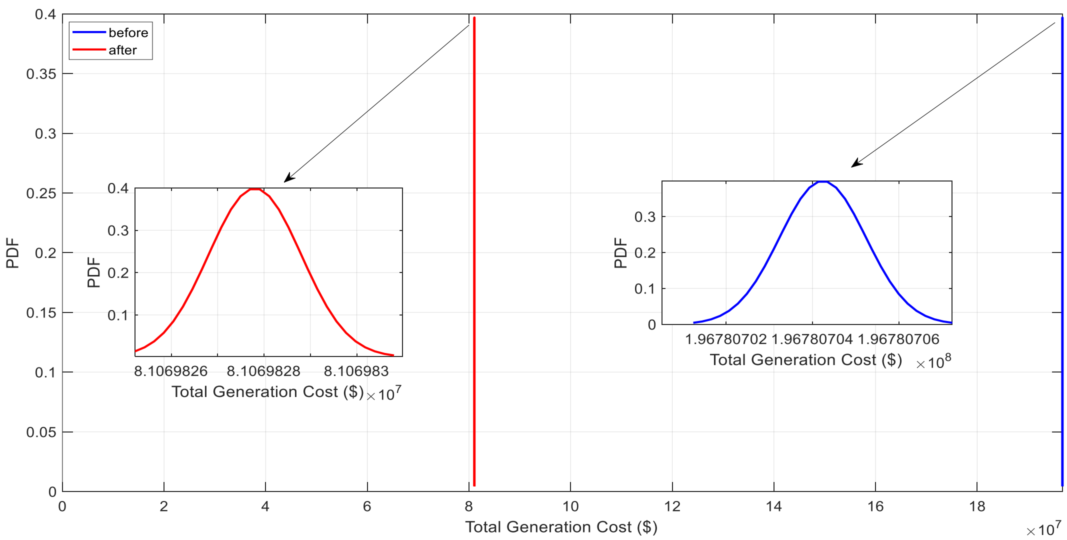

Fig. 14. Displaying the probability density function of production costs before and after optimal placement

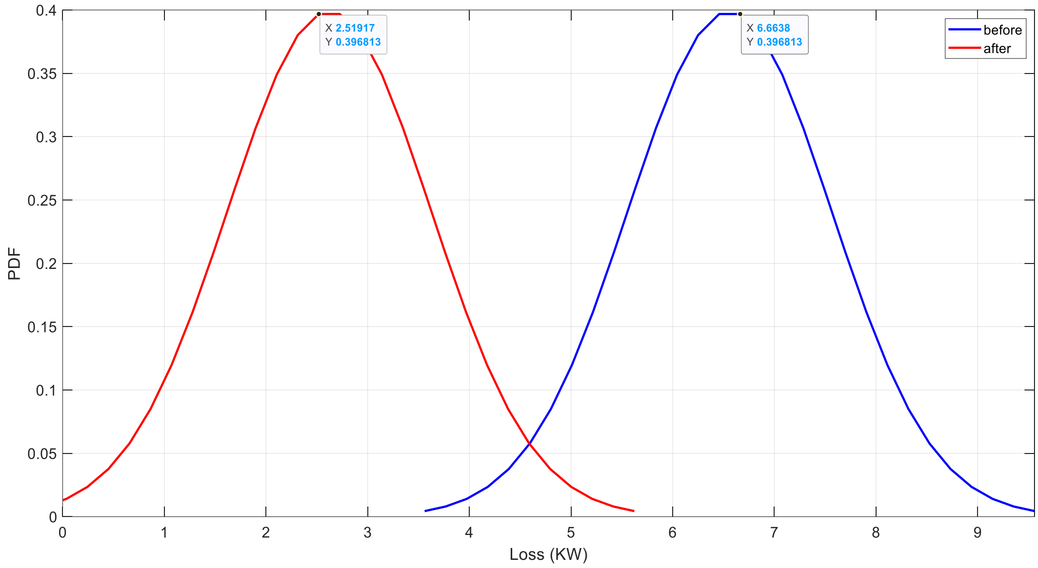

Fig. 15. Display of the PDF of the 24-hour total network losses before and after optimal placement.

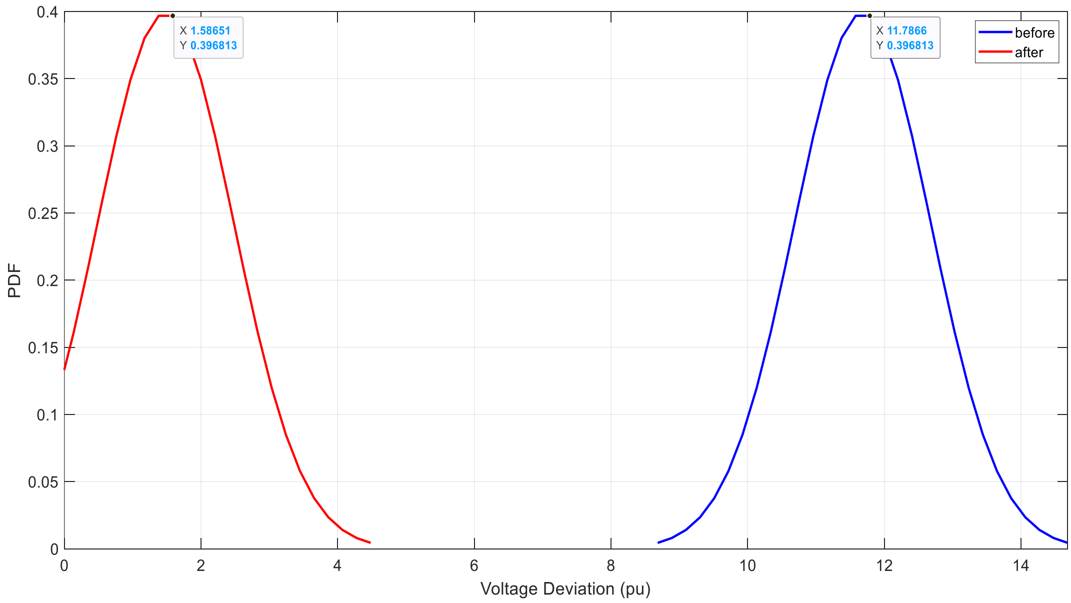

Fig. 16. PDF of the 24-hour total network voltage deviation before and after optimal placement

The results of comparing the performance of the proposed method with other previous approaches over a 24-hour research period, in terms of economic, reliability, and network security indices, are presented in Table (2) for the optimal placement of distributed generation resources.

As observed in Table 2, the proposed method demonstrates superior performance in both economic and technical indices of the network, even while considering reliability and security indices—factors that were overlooked in previous studies. This demonstrates how well the GWO algorithm can locate and scale DG resources inside the power network under study.

Table 2. Comparison of the proposed method with other recent modern methods following the implementation of the distributed generation placement program over a 24-hour period.

Indicator under study / Status under consideration	Operating cost (k$)	Losses (KW)	Voltage deviation (pu)	Expected Energy Not Supplied (EENS) (Kwh)	System overload capability (KW)	Short circuit level changes (pu)
Proposed method based on the Gray Wolf algorithm	196807.42	10.46	5.0	50.07	2079887.87	0.0027
	☑	☑	☑	☑	☑	☑
Adepoju et al [42]	197421.43	13.34	5.45	334.91	240750.58	0.23
Particle algorithm-based method	☑	☑	☑	☒	☒	☒
Selim et al [43]	197632.35	11.34	6.28	448.51	312526.61	0.12
Genetic algorithm-based method	☑	☑	☑	☒	☒	☒
Yu et al [44]	196979.61	-	-	-	-	-
Method based on the honey bee algorithm	☑	☒	☒	☒	☒	☒

5.Conclusion

An extensive overview of EVCSs and their importance in the power grid from a variety of angles is given in this study. Given the nature and attributes of EVs, the distribution level is where they are connected to the power grid. The term V2G refers to the combination of EVs as loads, energy suppliers, and storage units. But it's crucial to keep in mind that the grid may be significantly impacted by the concentration of EVs at charging points. It is necessary to examine the impact that charging stations have on the grid because they can behave as loads. Therefore, to enhance system stability and reduce outages, the negative effects of these charging stations—such as increased losses and voltage profile distortions—must be assessed, and strategies to mitigate these issues should be implemented.

Because of this, EV charging station placement is essential for avoiding voltage variations and network losses. This paper presents a method aimed at reducing losses and minimizing voltage deviations in the network while accounting for uncertainties and the probabilistic behavior of EV owners. It introduces a model for EV charging stations and defines an objective function for their optimal placement. This approach is grounded in queuing theory. To determine the optimal placement and capacity of EVCSs within the standard 33-bus distribution network, the proposed method is ultimately simulated and validated.

Due to differences in power distribution and power flow over the network lines, the simulation results show that the position of the EVCS inside the network has a substantial impact on the levels of losses and voltage deviations. Both GA and PSO were used in this paper to determine the best location for EVCSs. Because the network sees fewer voltage variations and losses when optimized using PSO as opposed to GA, the simulation results show that the PSO method works better than GA in identifying the ideal site.

References

[1] Ahmad. F, Iqbal. A, Asharf. I, Marzband. M, & Khan. I, Placement and Capacity of EV Charging Stations by Considering Uncertainties with Energy Management Strategies. IEEE Transactions on Industry Applications, 2023 ,59(3), 3865-3874.

[2] Hatami, Bayat, Peyman, Bayat, Pejman, & Tusi. A new strategy for managing electric vehicle energy based on a bidirectional three-port converter and fuzzy controller. Journal of Electrical Engineering, Tabriz University, 2016, 46(3), 121-137.

[3] Sadhukhan. A, Ahmad. M. S, & Sivasubramani. S, Optimal allocation of EV charging stations in a radial distribution network using probabilistic load modeling. IEEE Transactions on Intelligent Transportation Systems, 2021, 23(8), 11376-11385.

[4] Firoozmakan. P, Hoshmand. R, Khodabakhshian. A, Bornapour. M, Simultaneous energy management of Micro-CHP resources and energy storage in microgrids with responsive loads. Journal of Electrical Engineering, Tabriz University, 2019. 49(2), 753-765.

[5] Papadopoulos. P, Skarvelis-Kazakos. S, Grau. I, Cipcigan. L. M, & Jenkins. N, Predicting electric vehicle impacts on residential distribution networks with distributed generation. In 2010 IEEE Vehicle Power and Propulsion Conference, 2010, September, (pp. 1-5). IEEE.

[6] Sadhukhan. A, Sivasubramani. S, & Ahmad. M. S, Optimal placement of electric vehicle charging stations in a distribution network. In 2019 8th International Conference on Power Systems (ICPS), 2019, December, (pp. 1-6). IEEE.

[7] Fredriksson. H, Dahl. M, & Holmgren. J, Optimal placement of charging stations for electric vehicles in large-scale transportation networks. Procedia Computer Science, 2019, 160, 77-84.

[8] Reddy. M. S. K, & Selvajyothi. K, Optimal placement of electric vehicle charging stations in radial distribution system along with reconfiguration. In 2019 IEEE 1st International Conference on Energy, Systems and Information Processing (ICESIP), 2019, July, (pp. 1-6). IEEE..

[9] Reddy. M. S. K, & Selvajyothi. K, Optimal placement of electric vehicle charging station for unbalanced radial distribution systems. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 2020, 1-15.

[10] Yang. Q, Sun. S, Deng. S, Zhao. Q & Zhou. M, Optimal sizing of PEV fast charging stations with Markovian demand characterization. IEEE Transactions on Smart Grid, 2018, 10(4), 4457-4466.

[11] Arayici. K. C, & Poyrazoglu. G, The optimal placement model for electric vehicle charging stations. In 2019 International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET), 2019, August, (pp. 1-4). IEEE

[12] Ahmadian. A, Sedghi. M & Aliakbar-Golkar. M, Fuzzy load modeling of plug-in electric vehicles for optimal storage and DG planning in active distribution network. IEEE Transactions on Vehicular Technology, 2016, 66(5), 3622-3631.

[13] Shekari. T, Gholami, A & Aminifar. F, Optimal parking lot placement considering operational and security limitations using COA. In 2014 Smart Grid Conference (SGC) ,2014, December, (pp. 1-6). IEEE.

[14] Aghaebrahimi. M. R, Ghasemipour. M. M & Sedghi, AProbabilistic optimal placement of EV parking considering different operation strategies. In MELECON 2014-2014 17th IEEE Mediterranean Electrotechnical Conference. 2014, April, (pp. 108-114). IEEE.

[15] Shojaabadi. S, Abapour. S, Abapour. M & Nahavandi. A, Optimal planning of plug-in hybrid electric vehicle charging station in distribution network considering demand response programs and uncertainties. IET Generation, Transmission & Distribution, 2016, 10(13), 3330-3340.

[16] Liu. H, Hu. Z, Song. Y, Wang. J & Xie. X, Vehicle-to-grid control for supplementary frequency regulation considering charging demands. IEEE transactions on power systems, 2015, 30(6), 3110-3119.

[17] Torreglosa. J. P, García-Triviño. P, Fernández-Ramirez. L. M & Jurado. F, Decentralized energy management strategy based on predictive controllers for a medium voltage direct current photovoltaic electric vehicle charging station. Energy conversion and management, 2016, 108, 1-13.

[18] Poullikkas. A, Sustainable options for electric vehicle technologies. Renewable and Sustainable Energy Reviews, 2015, 41, 1277-1287.

[19] Wang. X, Shahidehpour. M, Jiang. C & Li. Z, Coordinated Planning Strategy for Electric Vehicle Charging Stations and Coupled Traffic-Electric Networks. IEEE transactions on power systems, 2019, 34(1), 268-279.

[20] Mozafar. M. R, Moradi. M. H, & Amini. M. H, A simultaneous approach for optimal allocation of renewable energy sources and electric vehicle charging stations in smart grids based on improved GA-PSO algorithm. Sustainable cities and society, 2017, 32, 627-637.

[21] Pal. A, Bhattacharya. A, & Chakraborty. A. K, Allocation of electric vehicle charging station considering uncertainties. Sustainable Energy, Grids and Networks, 2021, 25, 100422.

[22] Awasthi. A, Venkitusamy. K, Padmanaban. S, Selvamuthukumaran. R, Blaabjerg. F & Singh. A. K, Optimal planning of electric vehicle charging station at the distribution system using hybrid optimization algorithm. Energy, 2017, 133, 70-78.

[23] Deb. S, Gao. X.-Z, Tammi. K, Kalita. K & Mahanta. P, A novel chicken swarm and teaching learning based algorithm for electric vehicle charging station placement problem. Energy, 2021, 220, 119645.

[24] Guo. S, & Zhao. H, Optimal site selection of electric vehicle charging station by using fuzzy TOPSIS based on sustainability perspective. Applied Energy, 2015, 158, 390-402.

[25] Hussein. A. A, Capacity fade estimation in electric vehicle li-ion batteries using artificial neural networks. IEEE Transactions on Industry Applications, 2015, 51(3), 2321-2330.

[26] Kumar. B. A, Jyothi. B, Singh. A. R, Bajaj. M, Rathore. R. S, & Tuka. M. B, Hybrid genetic algorithm-simulated annealing based electric vehicle charging station placement for optimizing distribution network resilience. Scientific Reports, 2024, 14.1: 7637.

[27] Abdelaziz. M. A, Ali. A. A, Swief, R. A., & Elazab, R. A reliable optimal electric Vehicle charging stations allocation. Ain Shams Engineering Journal, 2024, 15.7: 102763.

[28] Pal. K, Verma. K, & Gandotra. R, Optimal location of FACTS devices with EVCS in power system network using PSO. e-Prime-Advances in Electrical Engineering, Electronics and Energy, 2024, 7. 100482.

[29] Yuvaraj. T, Arun. S, Suresh. T. D, & Thirumalai. M, Minimizing the impact of electric vehicle charging station with distributed generation and distribution static synchronous compensator using PSR index and spotted hyena optimizer algorithm on the radial distribution system. e-Prime-Advances in Electrical Engineering, Electronics and Energy, 2024, 8: 100587.

[30] Yao. W, Zhao. J, Wen. F, Dong. Z, Xue. Y, Xu. Y, & Meng. K, A multi-objective collaborative planning strategy for integrated power distribution and electric vehicle charging systems. IEEE transactions on power systems, 2014, 29(4), 1811-1821.

[31] Bae. S, & Kwasinski. A, Spatial and temporal model of electric vehicle charging demand. IEEE Transactions on Smart Grid, 2012, 3(1), 394-403.

[32] Xiang. Y, Liu. J, Li. R, Li. F, Gu. C & Tang. S, Economic planning of electric vehicle charging stations considering traffic constraints and load profile templates. Applied Energy, 2016, 178, 647-659

[33] He. F, Wu, D, Yin, Y, & Guan, Y. Optimal deployment of public charging stations for plug-in hybrid electric vehicles. Transportation Research Part B: Methodological, 2013, 47: 87-101

[34] M. Timouri, 2014, Queueing Theory (6th ed).

[35] Aghapour, Sepasian, & Mohammad-Sadegh, A probabilistic model for the optimal placement of fast charging stations

for electric vehicles. Scientific-Research Journal of Quality and Efficiency in Iran's Electricity Industry, 2018, 6.2: 11-24.

[36] Yudai. H, & Osamu. K, A safety stock problem in battery switch stations for electric vehicles. In Proc. 8th Int. Symp. Oper. Res. Appl.(ISORA), 2009, September, (pp. 332-339)

[37] Farkas. C, Szűcs. G, & Prikler. L, Grid impacts of twin EV fast charging stations placed alongside a motorway. In 2013 4th International Youth Conference on Energy (IYCE), 2013, June, (pp. 1-6). IEEE.