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Design of a Power Management Strategy in Smart Distribution Networks with Wind Turbines and EV Charging Stations to Reduce Loss, Improve Voltage Profile, and Increase the Hosting Capacity of the Network

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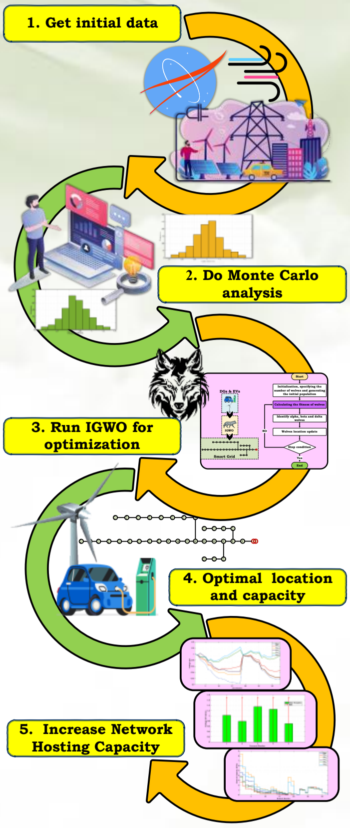
Highlight

- Increasing hosting capacity by utilizing green energy sources
- Uncertainty analysis using the Monte Carlo method
- Optimal design of smart grids based on the IGWO method

Graphical Abstract



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Design of a Power Management Strategy in Smart Distribution Networks with Wind Turbines and EV Charging Stations to Reduce Loss, Improve Voltage Profile, and Increase the Hosting Capacity of the Network

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ABSTRACT

Today, due to environmental and political reasons, countries around the world are required to use green energies, such as wind and solar energy. Also, most countries have switched to using electric vehicles (EVs) to reduce environmental pollution. Since smart distribution systems' distributed generation (DG) power output is limited, this paper addresses this issue by planning charging parking lots of EVs. The problem was formulated as a nonlinear optimization model. The objective function was to increase the power output, reduce the loss cost, and reduce the bus voltage deviations. Also, technical and economic limitations were considered in solving the planning problem. The uncertainty of consumption load, the behavior of EVs, and the output power of wind DGs were modeled using a combination of Monte Carlo and k-means methods. The improved gray wolf optimization (IGWO) algorithm was adopted to optimize the objective function. A standard IEEE 33-bus smart distribution system was studied to show the efficacy of the suggested solution. The results demonstrated the proposed solutions' high performance in improving the wind DG power output of the distribution system (PODS).

1. Introduction

Owing to technological advances, increasing environmental concerns, and efforts to reduce electricity costs, distributed generation (DG) in smart distribution systems is increasing. However, the DG power output of the distribution system (PODS) is limited. The growing use of solar and wind power plants, which are renewable energy sources, has highlighted the issue of their limited reliability compared to fossil fuel-powered generators. Consequently, there is a demand for energy storage devices. The power grid relies heavily on primarily producing electricity from thermal power plants, which, in turn, depend upon fossil fuels. This reliance is mostly due to the consistent and reliable energy generation they offer throughout each hour of the day. Unluckily, this reliability level is not yet achievable with clean wind and solar power plants.

The issue of poor reliability in solar and wind power plants can be mitigated by including electric vehicles (EVs). However, technological and economic constraints hinder the widespread adoption of these vehicles. This study demonstrates the impact of effectively integrating and managing renewable resources and EVs to enhance the system's power quality. The present study aimed to employ an emerging technology in the field of smart distribution systems that includes EV charging parking lots to enhance the DG power output of the smart distribution system. So far, many scholars have focused on increasing the DG power output of smart distribution systems.

Ref. [1] adopted an improved meta-heuristic optimization algorithm to optimally size and allocate DGs in a distribution system to finally enhance the power output of the smart distribution system. The results showed that resource planning could increase the power output of the 33-bus system by up to 4.5 MW. Ref. [2] improved the power output of a smart distribution system of solar cells by controlling the active and reactive power of solar cells and transformer tap changers.

Refs [3,4] analyzed a set of solutions for modeling the problem of improving PODS. They focused on three methods: stochastic planning, deterministic planning, and planning based on fuzzy logic and feasibility. The second and third methods were used to strengthen the PODS and protect the smart system by reversing the direction of the power flow through the main feeder. Refs. [5,6] determined the optimal DG power output of a smart distribution system based on the reactive power compensation approach by flexible AC transmission system (FACTS) devices in the distribution system. In the planning phase, they determined the optimal place and capacity of DG and reactive power compensators in the distribution system. Then, the optimal operation of DGs was addressed by considering the technical limitations of the distribution system in the operation phase.

Refs. [7,8] considered the challenges of the distribution system to accept DGs, including the constraints on the power flow in the feeders, the limitation of the bus voltage, the limitations of the power quality, such as the system's harmonics level, and also the limitations of the time coordination of the protective relays. These references considered the demand-side management programs, the utilization of electric energy storage devices, transformer tap-changer control, and reactive power control in the distribution system to be effective for improving DG PODS.

Refs. [9-11] evaluated distribution system reconfiguration methods to be economical and effective in improving PODS. However, solving this model was complicated due to the non-linearity of the optimization problem and the large size of real distribution systems. Therefore, they sought to design an innovative method to solve the problem.

Refs. [12-16] considered the presence of inverter-based DG as the cause of injecting harmonics in the system and sought to locate active filters in the distribution system with high DG penetration. In [17,18], two robust and smart methods were used for optimal management of the load in smart grids to enhance the voltage profile and shed the peak load. Both methods improved the system's load factor and the smart grid's performance and planning.

Refs. [19,20] studied methods for calculating the power output of the low-voltage distribution system. The authors considered that the power output evaluation methods included deterministic, probabilistic, and time-domain methods. These methods differed in accuracy, input type, time, and burden of calculations. Probabilistic methods were more optimal in uncertainties than conventional methods. Also, Ref. [21] dealt with locating and increasing the capacity of fast charging stations for EVs and DG in smart systems, taking urban traffic issues into account.

As is evident in the literature review, there are various techniques to improve DG PODS, such as DG planning, reactive power compensation, energy storage locating, reconfiguration planning [22], the application of FACTS devices [23], and voltage control and power factor control of resources and demand side load management. The present research proposed planning EV charging parking lots as a technique to boost the DG PODS. The goal was to evaluate the potential of planning EV charging parking lots to improve the wind DG PODS. Based on the literature review, some unresolved issues have not yet been explored by scholars and require additional investigation as a research concern.
This article delves into a few of these issues. The following are the research gaps:

- The concurrent integration of electric car capacity into the system alongside wind sources has been neglected.
- The ramifications and challenges it poses in the process of planning have not been acknowledged.
- The majority of the articles reviewed in this field are single-purposed.

Thus, based on the drawbacks identified in previous research, the present work has the following contributions and innovations:

- Taking the unpredictability of power demand, the availability of wind energy, and the presence of electric vehicles into account
- Employing the Monte Carlo approach to perform uncertainty calculations
- Utilizing the enhanced gray wolf algorithm

Section 2 discusses the formulation suggested for planning wind DG and EV charging parking lots. Also, the algorithm for solving the research problem, the method of modeling the uncertainties of the system load, the loading coefficient of the charging parking lots, and the wind speed are presented. Section 3 describes the studied distribution system and presents and analyzes the results. In the end, conclusions are provided in Section 4.

2. Materials and Approaches

Here, the problem of planning the presence of EV charging stations in smart distribution systems is discussed to enhance the power output and electrical parameters of the distribution system.

2.1. Objective function

Equation (1) shows the objective function.

$$MinF = -\sum_{i=1}^{N_b} C_1 \times Pdg_i + \sum_{i=1}^{N_b} C_2 \times \Delta V_i + \sum_{j=1}^{N_f} C_3 \times loss_j \quad (1)$$

where P_{dgi} represents the capacity of DG in bus I, i represents the bus number, N_b represents the total number of buses, j represents the index of branch counter, N_f represents the total number of feeders, $C_{1,2,3}$ represents the cost coefficients in the calculation of objective function terms, $loss_j$ represents the loss of feeder j, and ΔV_i represents the voltage deviation of bus i. As can be seen, the objective function in the optimization problem includes maximizing the total capacity of renewable DG installed in the distribution system buses, reducing the cost of losses, and reducing the voltage deviations of the system buses.

2.2. Constraints

To optimize the objective function, a set of economic and technical constraints are considered in the distribution system's operation, described below.

2.2.1. Consistency of active power in the entire system

According to Equation (2), the total active power generated in the system minus the total active loads must equal the system's total active losses.

$$P_{Generation} - P_{Load} = P_{Loss} \quad (2)$$

2.2.2. Consistency of reactive power in the entire system

According to Equation (3), the total reactive power produced in the system minus the total reactive loads has to equal the system's total reactive losses.

$$Q_{Generation} - Q_{Load} = Q_{Loss} \quad (3)$$

2.2.3. Active power balance in each bus

According to Equation (4), the total active power produced in the i-th bus (P_{Gi}) minus the total active power consumed in the i-th bus (P_{Di}) equals the total active power transferred from the i-th bus to the j-buses connected to this bus.

$$P_{G_i} - P_{D_i} = \sum P_{i\ to\ j} \quad (4)$$

2.2.4. Reactive power balance in each bus

According to Equation (5), the total reactive power produced in the i-th bus (Q_{Gi}) minus the total reactive power consumed in the i-th bus (Q_{Di}) equals the total reactive power transferred from the i-th bus to the j-buses connected to this bus.

$$Q_{G_i} - Q_{D_i} = \sum Q_{i\ to\ j} \quad (5)$$

2.2.5. Bus voltage limitation

According to Equation (6), the bus voltage (V_i) must be limited between V_{min} and V_{max}. According to IEEE standards, the bus voltage limit is set at 5% in this paper.

$$V_{imin} \le V_i \le V_{imax} \quad (6)$$

2.2.6. Limitation of heat capacity of the feeder

According to Equation (7), the power flow through the feeder should observe the thermal limit of the feeder.

$$fc_b < FC_{max} \tag{7}$$

This paper examines the thermal limit of the lines based on the highest apparent power flowing through them. The value of this limit is set at 1000 MVA for the lines.

2.2.7. Constraint of the total number of EV charging stations

According to Equation (8), the total number of EV charging stations that can be installed in the system buses (Nev) is limited to $N_{ev,max}$.

$$\sum_{ev=1}^{B_{ev}} N_{ev} \leq N_{ev,max} \tag{8}$$

2.2.8. Constraint of the maximum capacity of EV charging parking lots

Equation (9) states that the capacity of EV charging parking lots installed in the distribution system (CAP_{ev}) is limited to $CAP_{ev,\ max}$.

$$CAP_{ev} \leq CAP_{ev,max} \tag{9}$$

2.2.9. Limitation of candidate busses for installing EV charging parking lots

According to Equation (10), in all buses of the system (B) except for the buses that were candidates for installing charging parking lots (B_{ev}), the number of charging parking lots for EVs is considered equal to zero.

$$N_{ev} = 0 \ \ \forall ev \in B - B_{ev} \tag{10}$$

2.2.10. Constraint of the total number of DGs

According to Equation (11), the total number of DGs used in system buses (N_{dg}) is limited to $N_{dg,\ max}$.

$$dg{=}1BdgNdg{\leq}Ndg, max \tag{11}$$

2.2.11. Constraint of the maximum capacity of DGs

Equation (12) states that the total DG capacity installed in the distribution system is limited to $CAP_{dg,max}$.

$$CAPdg{\leq}CAPdg{,}max \tag{12}$$

2.2.12. Limitation of the number of candidate buses for installing DGs

According to Equation (13), the number of DGs is considered equal to zero in all the buses of the system (B) except for the buses that were candidates for the installation of DG (B_{dg}).

$$N_{dg} = 0 \ \ \forall dg \ \in B - B_{dg} \tag{13}$$

2.3. IGWO Algorithm

The improved gray wolf (IGWO) algorithm was introduced in 2018 [24]. This algorithm is a mathematical model derived from gray wolves' social behavior and hunting technique. The IGWO algorithm is a metaheuristic algorithm that mimics the social behavior of gray wolves during hunting by utilizing a hierarchical structure. The technique relies on demographic data, follows a straightforward procedure, and can be applied to more complex issues. The process consists of three primary stages:

- Observing, tracking, and pursuing the prey
- Approaching the prey closely, surrounding it, and deceiving it until it ceases its movement
- Attacking

The top three solutions in the IGWO algorithm are distinguished by α, β, and δ, respectively. ω characterizes the rest of the solutions. The GWO algorithm is guided by α, β, and δ, with ω subsequently following them. As previously stated, gray wolves besiege the prey. Equations (14) and (15) provide a mathematical representation of its action.

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)\right| \tag{14}$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \tag{15}$$

in which t is the current iteration, D is the track and direction vector, A and C are coefficient vectors, X_p is the prey position vector, and X is the position vector of a gray wolf. A and C vectors are calculated using Equation (16) and (17):

Here, t represents the current iteration, D denotes the track and direction vector, A and C represent coefficient vectors, X_p shows the prey position vector, and X represents the position vector of a gray wolf. The vectors A and C are computed using Equations (16) and (17).

$$\vec{A} = 2\vec{a}.\overrightarrow{a_1} - \vec{a} \tag{16}$$

$$\vec{C} = 2.\overrightarrow{r_2} \tag{17}$$

In Equation (16), a is decreased linearly from 2 to 0 during iterations, and r_1 and r_2 represent random vectors in the range of 0 and 1. As shown in Figure 1, a gray wolf's location is updated based on the prey's location.

The present position of various agents can be achieved by modifying the dimensions of vectors A and C. Consequently, a gray wolf can adjust its location within the vicinity of its prey by employing Equations (16) and (17) at random positions. The IGWO algorithm was presented to improve the original gray wolf algorithm. The basic algorithm has two flaws that could be enhanced [24].

The initial issue was related to the convergence factor, whereas the subsequent problem arose from a novel approach to determining the position of a wolf. This approach involved calculating the average of the motions of three specific wolves, namely alpha, beta, and delta. Enhancements were made to the two components of the GWO algorithm.

The convergence factor "a" exhibits a linear variation from 2 to 0 in the GWO algorithm. Nevertheless, the equation for the convergence factor was modified to Equation (18) to enhance detection and operation:

$$a = 2\left(1 - \left(\frac{t-1}{t_{max}}\right)^{1.5}\right) \tag{18}$$

where t represents the current iteration and t_{max} denotes the maximum number of iterations.

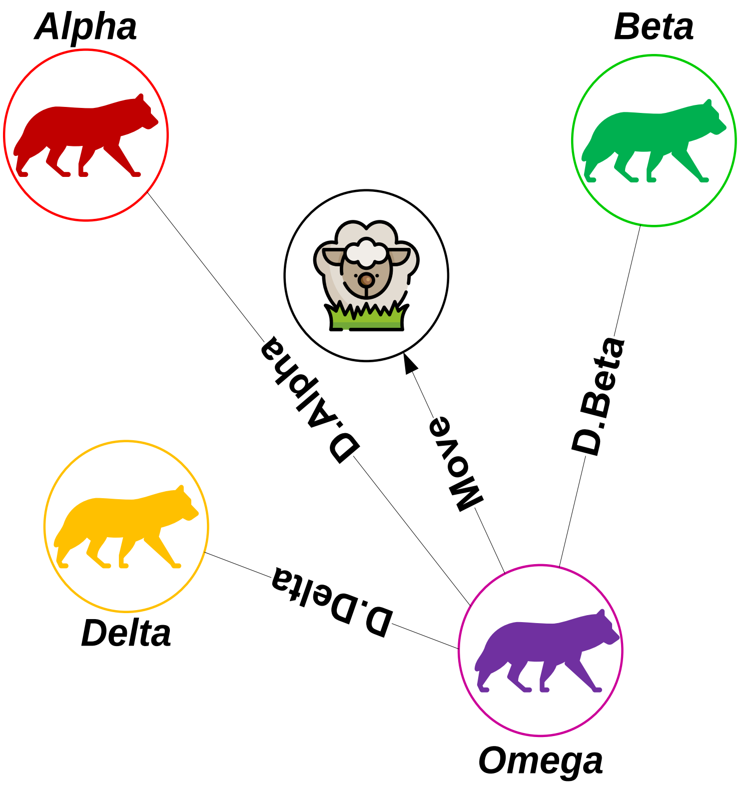

Figure 1. The IGWO position update [24].

The selection of the omega wolf's place in the hierarchy pyramid in the IGWO algorithm, as indicated by Equation (19), is mostly determined by the relative ranking of the three wolves.

$$X = X_{\alpha}.\left[\frac{Q(\alpha)}{Q(\alpha)} + Q(\beta) + Q(\delta)\right] + X_{\beta}.\left[\frac{Q(\beta)}{Q(\alpha)} + Q(\beta) + Q(\delta)\right] + X_{\delta}.\left[\frac{Q(\delta)}{Q(\alpha)} + Q(\beta) + Q(\delta)\right] \tag{19}$$

The new position of the gray wolf is calculated based on hierarchal weight, where the alpha wolf has more weight than the two other wolves. Q is wolf fitness in. Therefore, the omega wolf gets different weights from the three wolves according to their hierarchy. The gray wolf's new position is determined through hierarchical weighting, with the alpha wolf carrying greater weight than the other two wolves. The variable Q represents the fitness of the wolf in Equation (19). Consequently, the omega wolf receives distinct weights from the three wolves based on their order.

2.4. Uncertainty modeling

Uncertainties in the desired planning model include system consumption load, loading factor of the charging parking, and output power of wind DG. To model the uncertainty of the consumption load of the distribution system and the loading coefficient of the EV charging parking lot, the normal probability distribution function with the mean (μ) and standard deviation (σ) is used according to Equation (20):

$$f_{pd}(P_d) = \frac{1}{\sqrt{2\pi\sigma_d}} exp(-\frac{(P_d - \mu_d)^2}{2\sigma_d^2}) \tag{20}$$

Also, the Weibull probability distribution function is used to model the wind speed according to Equation (21) with parameters of shape factor c and scale factor k [25].

$$f_w(v) = \frac{k}{c}(\frac{v}{c})^{k-1}.exp\left[-(\frac{v}{c})^k\right] \tag{21}$$

The enhanced gray wolf method is a recent meta-heuristic algorithm that effectively solves multi-objective optimization problems. It has been extensively tested on many basic and complex functions in reference [24], yielding favorable results. Hence, in this study, given that our objective function is a three-objective function with numerous restrictions, it is advisable to employ this approach for its resolution.

3. Case Study and Results

3.1. Case Study

To show the effectiveness of the proposed solution, the standard IEEE 33-bus smart system with a single-line diagram was studied according to Figure 2. The backward-forward-sweep load flow approach is commonly employed for radial distribution systems. We employed this technique in the present work to execute load distribution [25].

To implement the simultaneous planning of wind DG and EV charging parking, it was assumed that all system busses, except for the primary substation, were candidates for installing DG and parking lots. The goal was to determine five buses in the system to install EV charging parking and five buses to install wind DG. The maximum capacity of EV charging parking lots in the entire system was considered 3.5 MVA. Also, the DG installation capacity in each bus was set at 2.5 MW. The study was carried out for one year, equivalent to 8760 hours. The expression of the objective function included the weighted sum of the cost of losses and the voltage deviations of the system buses minus the installed capacity of wind DG.

In evaluating the objective function expression, the cost of each kWh of losses was 4000 IRR, and the violation cost of each per-unit of system bus voltage deviations was 400 thousand IRR/h. If the power flow through the system feeders exceeded the thermal limit of the feeder (6.6 MVA), the objective function would be penalized 100 billion IRR. Uncertainties considered in solving the planning problem included the uncertainty in the system load, the load of EV charging parking lots, and the output power of wind turbines. To model the uncertainty of distribution system consumption, the normal distribution function was used with the mean and standard deviation values of 100% and 10%, respectively. Wind speed uncertainty was also modeled by the Weibull distribution function with shape and scale factor equal to 7 and 2, respectively.

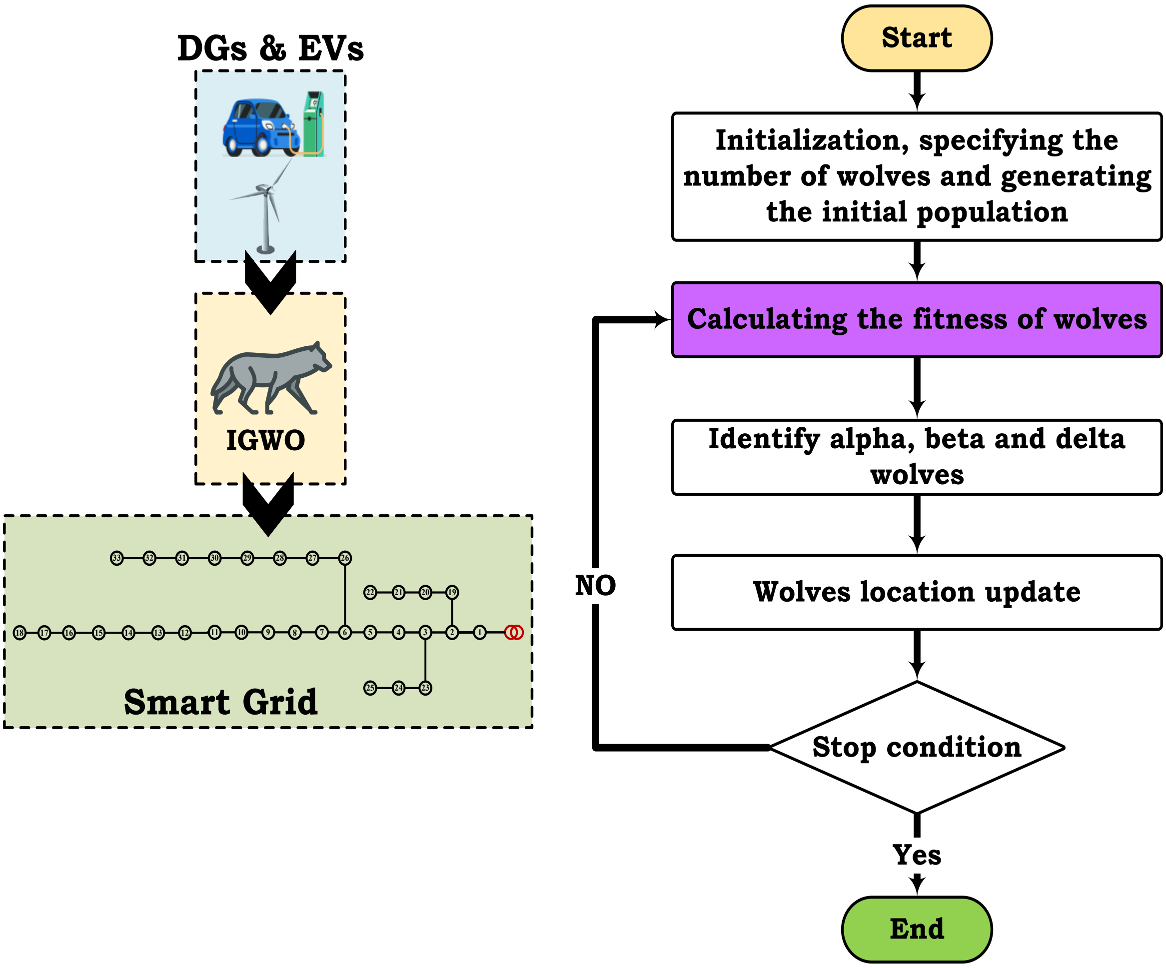

Figure 2. The standard IEEE 33-bus smart system and IGWO flowchart.

Also, the uncertainty of the charging profile of EVs was modeled with a normal distribution function with a mean and standard deviation of 70% and 20%, respectively. After designing the probability distribution functions with the mentioned parameters, a thousand samples were taken from each probability distribution function simultaneously with the *random* command. In this way, a 1000 × 3 matrix was built, in which the first to third columns show the system load factor, the EV charging parking lot load factor, and the wind turbine output power, respectively. Normally, it is unnecessary to study a thousand operation scenarios in a planning problem. To reduce the volume of calculations, the thousand scenarios generated from each variable with uncertainty were reduced to five scenarios using the data mining method. Figure 3-Figure 6 show the histogram curve of the system loading factor, charging parking loading factor, wind speed, and output power of the 500 kW (0.5 MW) wind turbine obtained by taking a thousand samples from specific probability distribution functions, respectively. By applying the *k*-means algorithm to 1000 samples, 5 scenarios of system load factor, charging parking load factor, and wind turbine output power of 500 kW were obtained according to Figure 7-Figure 9. Also, the probability of the occurrence of each scenario is shown in Figure 10.

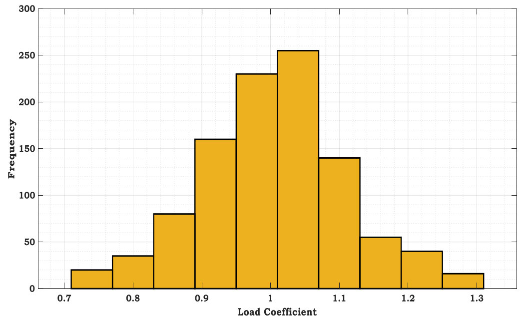

Figure 3. The system's load factor.

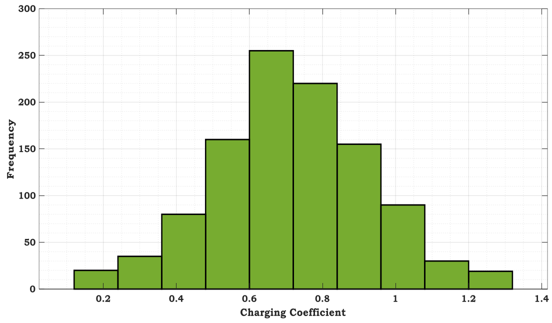

Figure 4. The loading coefficient of the parking lot.

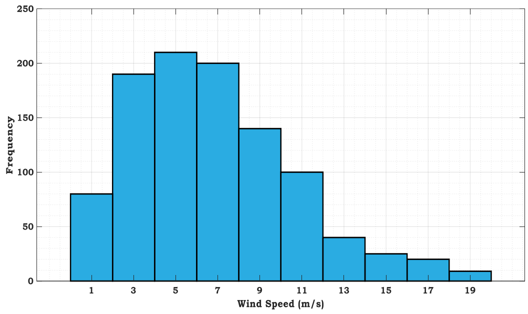

Figure 5. Wind speed.

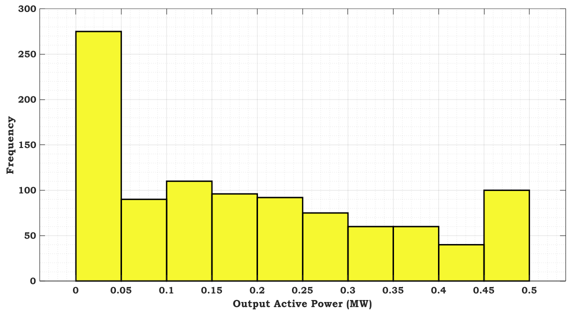

Figure 6. Wind turbine output power.

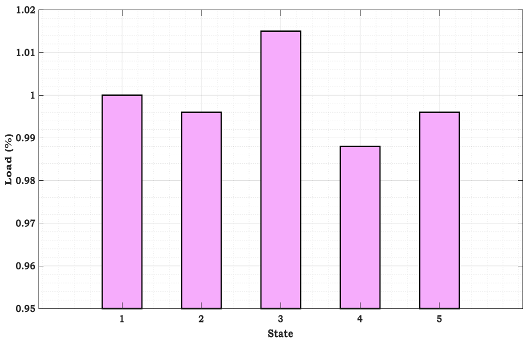

Figure 7. The system's load profile.

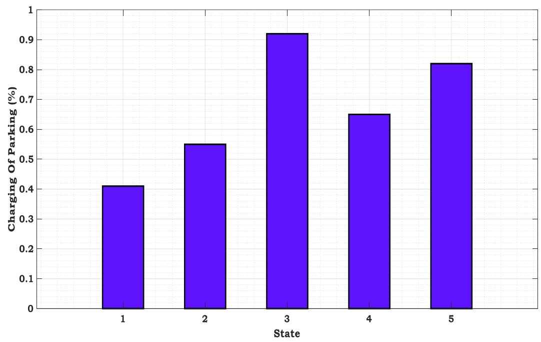

Figure 8. Charging profile of charging parking lots.

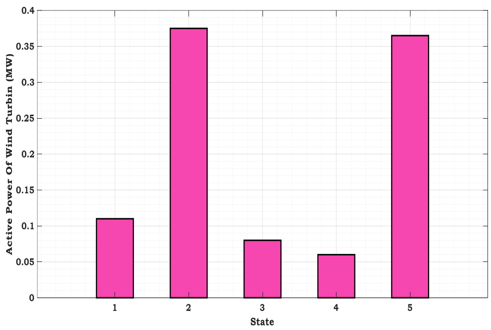

Figure 9. Active output power profile of the 500-kW wind turbine.

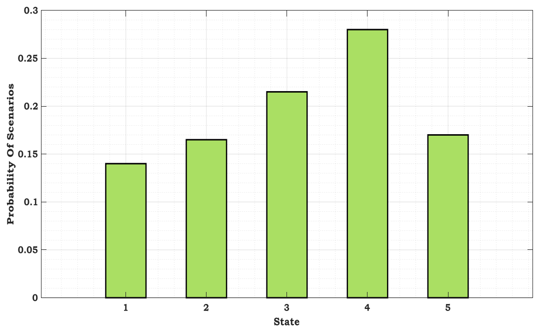

Figure 10. The probability of the occurrence of scenarios.

Table 1 provides a summary of the implementation considerations of the proposed solution. The proposed solution is simulated below by considering five possible scenarios. To perform the optimization, the gray wolf algorithm whose settings are presented in Table 1 and Table 2 was used.

3.2. Analysis of results

This section discusses the simulation of the suggested solution. The aim was to find the place and size of EV charging lots and wind DG optimally to improve the DG PODS and reduce operating costs. Figure 11 shows the improvement process of the objective function. In this curve, the horizontal and vertical axes represent the number of iterations and the objective function, respectively. Also, Table 3 and Table 4 show the optimal solution, including the place and size of the charging parking and wind DG. The optimal capacities were set as the maximum installation capacity of DG, which was used according to uncertainty coefficients in operating conditions. The distribution system's performance was evaluated after applying the optimal solution to the distribution system. Figure 12 to Figure 15 show the bus voltage curve, the power flow through the feeders of the distribution system, the losses of the feeders of the distribution system, and the voltage deviations of the system buses in the optimal state compared to the normal state, respectively.

Table 1. Technical and economic data of the hybrid energy system component.

Parameter	Value
Candidate buses for charging parking	Buses 2 to 33
Candidate buses of wind turbines	Buses 2 to 33
Maximum capacity of the charging parking lot	3.5 MWA
The total capacity of wind turbines in the bus	2.5 MW
C_1 coefficient	1000
C_2 coefficient	400 thousand IRR/per-unit hour
C_3 coefficient	10 billion IRR
The cost of losses	4000 IRR/kWh

Table 2. Optimization algorithm settings.

Variable	Value
The number of iterations	50
Population size	100
r_1 coefficient	Rand [0,1]
r_2 coefficient	Rand [0,1]

Table 3. Optimal location and installation capacity of charging parking lots.

Bus number	21	20	9	19	25
Capacity (kW)	490	830	370	590	180

Table 4. Optimum location and installation capacity of wind DGs.

Bus number	18	3	19	9	20
Capacity (MW)	1.7	3.9	2.9	2.5	4.05

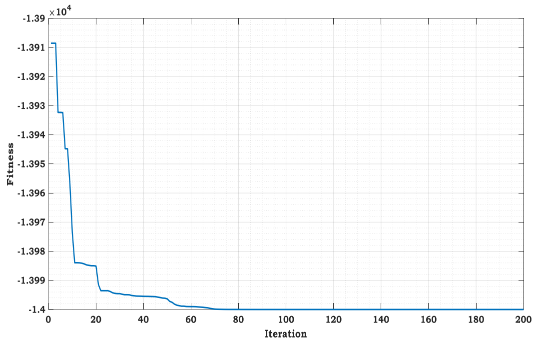

Figure 11. The process of improving the objective function.

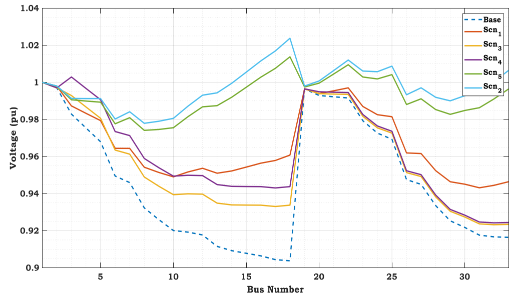

Figure 12. Voltage curves of distribution system buses in five uncertainty events.

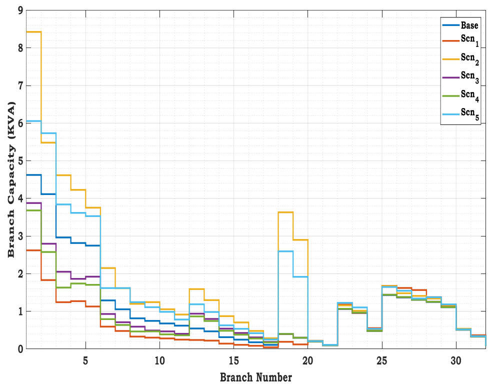

Figure 13. Power flow through distribution system feeders in five uncertainty events.

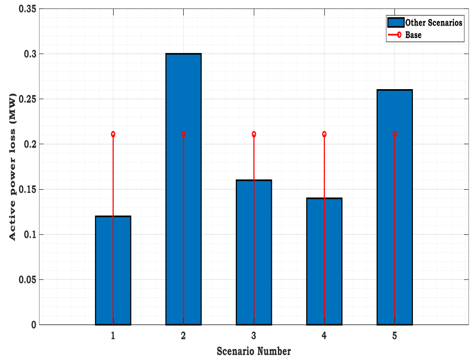

Figure 14. Comparison of losses of distribution system feeders in different states of uncertainty.

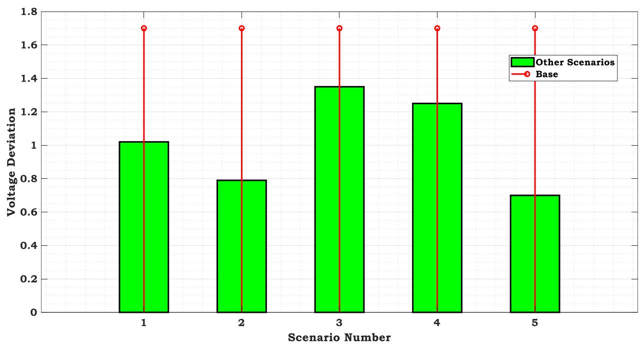

Figure 15. Comparison of voltage deviations of distribution system buses in different states of uncertainty

Accordingly, the voltage curve of the system buses improved considerably. Also, the power flow through the system feeders was such that it followed the thermal restrictions of the system feeders, which was 6.6 MVA. According to the results, the losses of system feeders in the second and fifth scenarios increased compared to the primary distribution system. Nonetheless, the loss of the whole system was improved compared to the initial state. It should be noted that in the process of evaluating DG PODS, system losses should not increase from the initial value.

4. Conclusions

The research aimed to plan EV charging parking lots to improve the electrical parameters of the smart distribution system and increase the wind DG PODS. The problem was formulated as a nonlinear optimization model. The objective function included reducing losses, reducing voltage deviations, and increasing the power output of the smart system. In solving the optimization problem, a set of technical and economic constraints were considered. To achieve robust optimal solutions, the uncertainties of charging parking lots, smart grid consumption, and wind speed were modeled by combining Monte Carlo and *k*-means methods. The gray wolf algorithm was adopted to address the optimization problem. Studies were done on the standard IEEE 33-bus smart system to demonstrate the effectiveness of the proposed solution. The results showed the high efficiency of the proposed solution.

In summary, the following outcomes were achieved:

- Employing the enhanced gray wolf algorithm for solving the multi-objective problem
- Taking several uncertainties related to wind resources, load, and cars into account
- Evaluating the outcomes with the clustering technique

Prospective projects and concepts:

- Utilizing alternative meta-heuristic techniques to address the problem and subsequently comparing the outcomes
- Taking the availability of solar resources in the power grid into account
- Implementing an electric spring in the system to enhance electrical flexibility

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

Credit Authorship Contribution Statement

Javad Ebrahimi: Conceptualization, Formal analysis, Project administration, Supervision, Validation, Roles/Writing - original draft. **Mahyar Abasi:** Conceptualization, Investigation, Methodology, Resources, Visualization, Writing - review & editing.

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