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Electric vehicle charging stations location optimization in distribution systems using meerkat optimization algorithm

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ABSTRACT

The meerkat optimization algorithm (MOA) is used in this study to suggest an effective multi-objective optimization framework for the best location and dimensions of electric vehicle charging stations (EVCSs) in radial distribution systems (RDS). The performance of the system in terms of power loss and voltage stability is significantly affected the growing prevalence of EV loads. To reduce the real power losses and average voltage deviation index (AVDI) while improving the voltage stability index (VSI), a multi-objective function was developed. The IEEE 69-bus system is subjected to various loading conditions using the recommended MOA, which is distinguished by its balanced exploration-exploitation process and parameter-free structure. In comparison with the basic and current methodologies, simulation findings show that the recommended approach improves the voltage profile, decreases power losses, and enhances the VSI. The advantages of the MOA in terms of convergence time, solution quality, and resilience were confirmed by a comparison with the HBA, TLBO, ALO, and FPA. The results confirm that the suggested approach is effective for modern EV-integrated distribution networks.

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1. INTRODUCTION

The rapid adoption of electric vehicles (EVs) has brought both challenges and opportunities to contemporary power distribution networks. EVs have the potential to significantly reduce greenhouse gas emissions and fossil fuel reliance when combined with low-carbon sources of electricity. However, widespread EV charging introduces additional time-varying loads on distribution feeders, which increase peak demand, voltage deviation, line losses, and can cause coordination problems in protecting equipment, especially in radial distribution systems, which are common in residential services and rural settings. Therefore, the strategic locations and size of EV chargers have become a major challenge in planning, which directly effects the performance of power systems, accessibility, and economic feasibility of electrified transportation. This study addresses these challenges by proposing a metaheuristic optimization approach for sizing and locating EV charging station (EVCS) in radial distribution systems (RDS).

Both classical algorithms and soft-computing strategies have been examined in current research to optimize the location of EVCS in radial distribution systems (RDS). To ease congestion, reduce charging costs, and minimize network losses, [1] employed particle swarm optimization (PSO). Voltage stability is significantly enhanced when photovoltaic (PV) generation is integrated into metropolitan systems. To lower energy losses and capital expenses, result in [2], [3] suggested a siting strategy for fast charging stations. A bi-level mixed-integer programming model was presented in [4] for EVCS siting and operational control in transport networks. Meanwhile, PSO was used by [5] to precisely locate fuel cell stations and allocate capacities among intra-city distribution lines. Ahmad *et al*. [6] used a hybrid GA-SAA to strategically determine the ideal PEVCS locations to solve the integration challenge. In addition, Hashemian *et al*. [7] demonstrated that integrating EV fast-charging points into a dynamic bus service in Luxembourg can be achieved using a surrogate-assisted optimal technique. Given its impact on system reliability, expenses, and sustainability footprints, the continuous integration of EV charging station (EVCS) infrastructure into distribution networks continues to pique interest [8]. A study in [9] used traffic flow data and a mixed-integer linear programming model to fine-tune fast-charging station siting via GAMS, and a study in [10] used a genetic algorithm to reduce power losses through the grid. Meanwhile, for the IEEE 33 test system, the probabilistic control architecture provided in [11] integrates voltage stability measurements and load variability considerations.

An arithmetic optimization algorithm was proposed in [12] to enhance the placement of EVCSs connected to power plants. This method was superior to both PSO and HHO. Distribution-level ESS installation increases voltage control more effectively than centralized systems, fulfilling the voltage compliance limitations established by grid codes. The study in [13] assesses distributed ESS integration on power quality using NEPLAN. The study in [14] uses the IEEE 69 bus standard and the BFOA-PSO algorithm, whereas [15] uses a node-selection hierarchy to hasten the commercial penetration of EVs. To support voltage stability, a study in [16] integrated distributed generators into the distribution system (URDS), and a study in [17] provided a framework that combined the deployment of EVCS with transmission network (TN) and distribution network (PDN) designs. To perform an impact analysis, the studies in [18], [19] used stability indices in conjunction with 24-hour load profiles.

Although many studies have been conducted on EVCS allocation utilizing metaheuristic techniques, current methods frequently have limited exploration capabilities, premature convergence, and difficult parameter tweaking. These restrictions are addressed by the recommended meerkat optimization algorithm (MOA), which uses a two-phase adaptive search mechanism that guarantees efficient local exploitation and global exploration without the need for algorithm-specific parameter tweaking.

The key contributions made by this work are: i) Development of an EVCS allocation model with several objectives that considers power losses, VSI, and AVDI; ii) The use of the MOA for EVCS placement in RDS has not been thoroughly investigated in the literature; iii) The performance of the MOA was benchmarked by a thorough comparison with HBA, TLBO, FPA, and ALO; and iv) Validation of the IEEE 69-bus system under various EV penetration scenarios.

2. PROBLEM FORMULATION

This study examines the impact of EV integration on RDS. EVs act as additional loads on the system and thus reduce the voltage profile and VSI, reactive and real power losses, and introduce voltage variations. These issues can be resolved by defining the problem as the optimization of a large number of goals, which are the reduction of the power loss and voltage variation loss and improved voltage profile of the system coupled with the VSI. A radial distribution system's (RDS) load flow is solved using the BW/FW LF approach [20].

2.1. Multi-objective function

Here is a mathematical description of the suggested multi-objective optimization function.

$$MOF = min\,(w_1 f_1 + w_2 f_2 + w_3(\tfrac{1}{f_3})) \tag{1}$$

The (2) defines the RDS's real power losses, which are based on the proposed test system's reactive and real power flow.

$$f_1 = P_{loss} = \sum_{k=1}^{nl} \frac{r_{ij}(P_j^2 + Q_j^2)}{V_i^2} \tag{2}$$

The second goal, which is expressed mathematically in (3), is to lower the AVDI.

$$f_2 = AVDI = \frac{1}{NB} \sum_{I=1}^{NB} |1 - V_i| \tag{3}$$

Enhancing the proposed test system's VSI is the third goal, which is described as (4).

$$f_3 = VSI_j = [|V_i|^4 - 4(P_j x_{ij} - Q_j r_{ij}) - 4(P_j r_{ij} + Q_j x_{ij})|V_i|^2] \quad (4)$$

Where r_{ij} is the resistance of the branch "ij", x_{ij} is the "ij" branch reactance, V_i is the ith bus voltage, P_j is the overall real power requirement at the jth bus, and Q_j is the overall demand for reactive power at the jth bus. Weighted aggregation is used to convert the multi-objective function into a single-objective form. The normalized objective values and system performance priorities are used to select the weighting factors.

2.2. System constraints

The recommended multi-objective function, as stated in (4), is lowered while considering operational restrictions on branch power flows (|Si|) and node voltages (Vi), as well as design restrictions on charging stations (CSs), such as the quantity of charging stations (CSs) and charging points (CPs), as specified in (5)-(8). Branch current limits are indirectly enforced through apparent power constraints and voltage limits to ensure safe system operation.

- Constraints on voltage limit

$$V_{min} \leq V_i \leq V_{max} \qquad i=1,2,\ldots nb \quad (5)$$

- Constraints on total power limit

$$|S_l| \leq |S_{l,max}| \qquad l=1,2\ldots.nbl \quad (6)$$

- Limitations on charging points

$$nCP_{min} \leq nCP \leq nCP_{max} \quad (7)$$

- Charging stations limit constraints

$$nCS_{min} \leq nCS \leq nCS_{max} \quad (8)$$

3. MEERKAT OPTIMIZATION ALGORITHM

The meerkat optimization algorithm (MOA) [21] is a recently developed metaheuristic technique that was proposed as a method for identifying the location of EVCSs in a RDS. The IEEE 69-bus test system was chosen as the study network because of its appropriateness for studying the medium-voltage distribution performance under different load conditions. The algorithm models the lookout and cooperative behavior of meerkats to perform optimization, where they use vigilance and coordinated group behavior that focuses on the prey. The optimization process is based on these strategies.

- Step 1: The IEEE 69-bus system network and load data were gathered along with the line parameters, base loads, and operating limits. The profiles of the representative EV charging demands were formed under low-, medium-, and high-penetration conditions. The voltage and loss behaviour were analysed by modelling the system in a MATLAB environment using suitable power flow analysis routines.
- Step 2: The parameters of the problem were stated by determining the feasible buses on which the charging stations were to be installed and the maximum limits through which the charging stations would be determined. The analysis was performed on both placement-only and placement-with-sizing cases based on the circumstances involved.
- Step 3: The aim of the optimization was to decrease voltage variations and active power loss and meet other operational requirements, including voltage constraints, line loading, and investment capacity. The problem was coded into a decision vector, which is the possible station areas and sites.
- Step 4: The meerkat optimization algorithm was initiated with several random candidate solutions in its population. The candidates are potential arrangements of EV charging stations in the network. Fitness was assessed by running power-flow analyses of all candidates and calculating their performance indices.
- Step 5: The MOA search activity switches between exploration and exploitation stages. New candidate solutions were produced during exploration by making random alterations to ensure that a wide range of solutions were searched. In exploitation, the solutions that performed well were tweaked to improve their performance. The use of constraint handling strategies ensured the maintenance of feasibility through the repair of infeasible solutions or penalization.
- Step 6: This was repeated until convergence was reached or until the maximum limit of iterations was reached. The obtained optimal solution was discussed with regard to bus positions, station capacity, voltage

profile elevation, and minimization of losses. A base case was used to perform a comparative analysis and prove the effectiveness of the suggested approach.

3.1. Addressing the EVCSs allocation problem with the MOA technique

- Initialization: Input network data and system parameters. The IEEE 69-bus system configuration and bus load data are used as the base for optimization.
- Candidate solution generation: The meerkat optimization algorithm generates random solutions by suggesting different possible placements for EV charging stations.
- Fitness evaluation: Each candidate solution is evaluated using power flow analysis (usually backward-forward sweeps for radial networks), targeting the reduction of power losses and increment of voltage profiles.
- Meerkat algorithm cycles: The algorithm performs exploration (searching broadly across the solution space) and exploitation (focusing the search around promising solutions), updating the population iteratively.
- Convergence check: The algorithm checks if the objective function meets the convergence criteria or maximum iterations are reached. If not, solution updating continues.
- Output: The locations (bus numbers) of the proposed optimal EV charging stations are selected, enabling practical deployment in the IEEE 69-bus system.

3.2. Computational complexity

In addition to solution quality, computational efficiency is an important factor when assessing optimization algorithms for real-world power system applications. The population (N), number of iterations (T), and load flow calculations affect the computational complexity of the MOA. The overall complexity can be approximated as O ($N \times T \times LF$), where LF represents the complexity of load flow calculations. Owing to its adaptive search procedure, the MOA exhibits faster convergence despite iterative evaluation.

4. RESULTS AND DISCUSSION

The applicability of the proposed MOA was evaluated on the IEEE 69-node test system, and the data related to the lines and buses of the test system were acquired from [22]. The simulations were performed in MATLAB 14.0 and run on a PC with the following specifications: Intel Core i5-4210U CPU (maximum of 2.5 GHz) and 8 GB RAM. The study considers battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) and the design of appropriate charging points (CPs) to serve both. Table 1 lists the design features of the EV-CSs. Table 1 presents the characteristics of EVs, including their power ratings and charging stations specifications. Table 1 shows that the CSs have a power rating of a minimum of 975 kW and a maximum of 1674.5 kW.

Table 1. EV and CS features for the simulation

Type of EV	CS's Rating (kW)		Power rating of EV (kW)	No. of CPs	
	Min	Max		Min	Max
Chang An Yidong	75	112.5	3.75	20	30
Chevrolet Volt	55	77	2.2	25	35
BMW i3	440	880	44	10	20
SAE J1772 standard	210	280	7	30	40
Tesla model X	195	325	13	15	25
CS's overall power rating in kW	975	1674.5			

4.1. Test system: 69-node test system

The suggested MOA was tested for its performance and efficiency based on the IEEE 69-node test system, and the system and load parameters were obtained from [23]. This network has a 12.66 KV rating and an overall load of 3801.4 kW (active current) and 2693.6 kVAr (reactive current). The parameters used in the MOA were seven variables, 200 iterations, and 50 individuals in the population size.

The proposed system was tested in five scenarios. Case-1 considers the base distribution load flow. Case-2 posed a greater demand than Case-3 with the minimum number of CPs in the lowest rating of CS and the highest number of CPs in the full rating of CS, respectively. Case-4 identifies the best EVCS placement based on the MOA with the lowest number of CPs, and Case-5 identifies the best EVCS placement based on the highest number of CPs at the maximum rating.

Case-1 was a distribution load flow analysis to determine the power loss, minimum voltage, VSI, bus voltages, and AVDI. In Case-2, the system load increases, and the three EV-CSs (one per sub-feeder) with minimum CPs impose three-quarters of Case-1 load of 2925 kW (1.7695 times) on the system load as opposed to Case-1, which is 3801.4 kW. As such, the power losses increased from 224.8807 to 613.4994 kW (72.81 higher), AVDI was now 0.004 as opposed to 0.0014, VSI decreased to 0.5114 as opposed to 0.6823, and the minimum voltage was now 0.84620 p.u. as opposed to 0.90920 p.u. When the maximum number of CSs (three) is used in Case-3, the system loading increases to 8824.9 kW (instead of 3801.4 kW), which is 2.3215 times higher than Case-1. Consequently, the actual losses increased from 224.8807 to 1108.6 kW (292.97 more than Case-1 and 172.81 more than Case-2), but the AVDI increased from 0.0014 to 0.0072. The VSI decreases to 0.39490 of the previous 0.68230, and the minimum voltage at bus-65 decreases to 0.79350 p.u. of 0.90920 p.u.

The recommended MOA was applied to Cases 3 and 2 to determine the best allocation of CS, as in Cases 5 and 4. Based on the 6640 kW total load demand in Case 4, the MOA identified that buses 2, 25, and 4 were the best places to ensure the least number of CPs. The losses dropped to 219.1645 kW, AVDI to 0.001364 as compared to 0.0040, and VSI to 0.690812 as compared to 0.5114, respectively. Vmin also improved to 0.9096 p.u. compared to 0.8462 p.u. Figures 1 and 2 depict the VSI and voltage profiles of Case 4 and the base case, respectively.

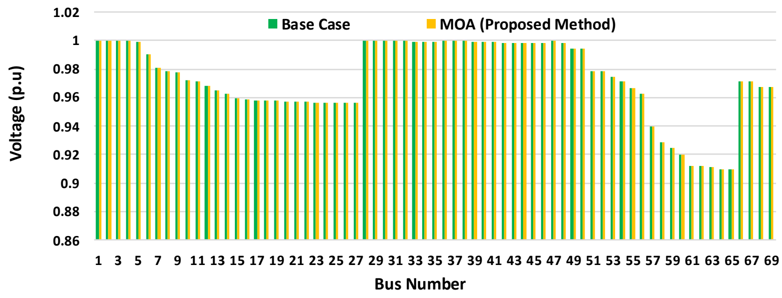

Figure 1. Voltage profile of 69-bus system

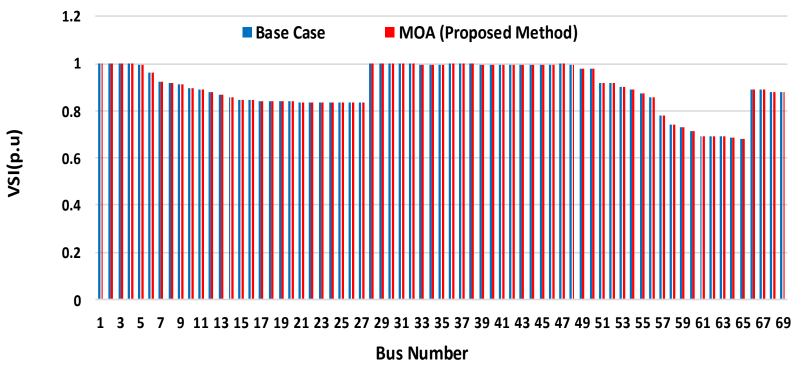

Figure 2. VSI of 69-bus system

In Case-5, the MOA provides the best CS locations at buses 2, 25, and 4 and minimizes losses in the system at 1108.6266 to 219.8421 kW, AVDI 0.0013 to 0.0072, and VSI 0.690642 to 0.3949. The lowest voltage was also improved to 0.9094 p.u., compared to 0.79350 p.u. All scenarios resulted in a summary of the outcomes, which are summarized in Table 2. The power losses in Cases 4 and 5 (219.1645 and 219.8421 kW, respectively) were considerably reduced compared with those in Cases 2 and 3. Figure 3 shows the convergence curve of the 69-bus system. Figure 4 shows the power loss comparison of MOA with existing methods.

4.2. Discussion

The findings unequivocally show that integrating EVCS without optimization (Cases 2 and 3) causes a significant decline in the system performance, including higher power losses and worse voltage stability. However, the application of the MOA (Cases 4 and 5) significantly restored the system performance by optimally locating the EVCSs. In Case 4, the MOA achieved 2.7% less power loss than the best approach currently in use (HBA: 225.17 kW vs. MOA: 219.16 kW) when compared to HBA, TLBO, ALO, and FPA. A 35% improvement in the VSI from 0.5114 (case 2) to 0.6908 (case 4) directly decreses the probability of voltage collapse. A more uniform voltage profile was confirmed by the AVDI drop from 0.0040 to 0.001364 (66% lower). The reduction in power losses and improvement in the VSI demonstrated the effectiveness of the recommended algorithm. MOA demonstrated greater exploration capabilities by achieving reduced losses and improved voltage stability compared to FPA, ALO, TLBO, and HBA.

Table 2. Simulation outcomes of 69-node test system

Cases and load	Techniques	Locations of EV charging stations	Power losses (kW)	AVDI (p.u.)	VSI (p.u.)	V_{min} (p.u.)
Case 1 (3801.4 kW) (Base Case)	-		224.97	0.0014393	0.683323	0.9092
Case 2 (6726.4 kW)	-		613.4994	0.004	0.5114	0.8462
Case 3 (8824.9 kW)			1108.6266	0.0072	0.3949	0.7935
Case 4	MOA (proposed)	2, 25, 4	219.1645	0.001364	0.690812	0.9096
	HBA [24]	2, 28, 3	225.1700	0.0014402	0.683274	0.9092
	TLBO [25]	2, 28, 47	225.2186	0.0014	0.6822	0.9092
	ALO [25]	2, 28, 47	225.2186	0.0014	0.6822	0.9092
	FPA [25]	2, 28, 47	225.2186	0.0014	0.6822	0.9092
Case 5	MOA (proposed)	2, 25, 4	220.8421	0.001382	0.690642	0.9094
	HBA [24]	2, 28, 3	225.4122	0.0014493	0.683052	0.9092
	TLBO [25]	2, 28, 47	225.5766	0.0014	0.6821	0.9092
	ALO [25]	2, 28, 47	225.5766	0.0014	0.6821	0.9092
	FPA [25]	2, 28, 47	225.5766	0.0014	0.6821	0.9092

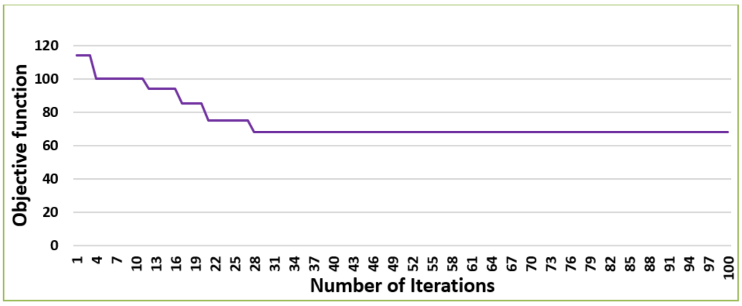

Figure 3. 69-node test system convergence curve

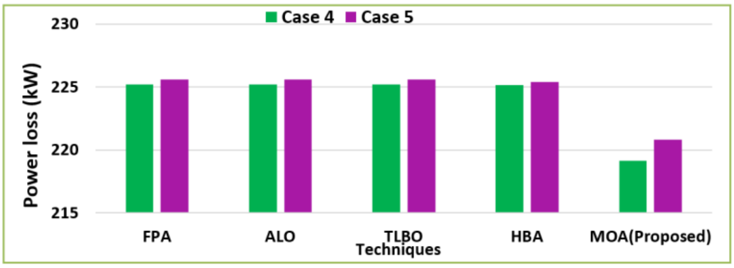

Figure 4. Power loss comparison of MOA with existing methods

5. CONCLUSION

A new stochastic search method called MOA is proposed as an effective optimization approach for the optimization of EVCSs positions in radial distribution systems. The MOA has both exploration and exploitation steps to find an optimal solution with a shorter computational time. The MOA was tested on a 69-bus test system, and it was reported that the optimal locations of the EVCS were determined, which resulted in significant improvement in system performance. These findings indicate a significant reduction in actual power losses, voltage profile improvement, reduction in AVDI, and improvement in VSI. A comparative analysis with existing metaheuristic approaches, such as HBA, FPA, ALO, and TLBO, showed that MOA demonstrated a lower computational time and higher accuracy in providing solutions and was more reliable. These results affirm that MOA is a powerful and effective optimization tool for solving complex power system issues, including the allocation of power distribution networks in EVCSs. Despite its efficacy, real-time uncertainties, such as stochastic EV behavior, are not considered, and the recommended solution is only tested on a conventional IEEE test system. Future research should focus on the following aspects: i) combining machine learning approaches with MOA, ii) combining renewable energy sources, iii) utilization in real large-scale distribution systems, and iv) dynamic EV load modelling in real-time.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [MT], upon reasonable request.

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