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Impacts of electric vehicle charging stations and DGs on RDS for improving voltage stability using honey badger algorithm

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ABSTRACT

The intelligent computational technique used in this research handles the multi-objective voltage stability optimization (MOVSO) problem in radial distribution systems (RDS). The objectives of the proposed research are to minimize network loss, lower the average voltage deviation index (AVDI), and improve the voltage stability index (VSI) of RDS by taking into account the recently created distributed generators (DGs) and electric vehicle charging stations (EVCSs). To address the MOVSO problem, a novel and innovative honey badger algorithm (HBA) optimization technique is put forth. The two stages of HBA, known as the "digging" and "honey" phases, are responsible for effectively identifying the ideal position and appropriate quantity of EVCSs and DGs. The standard IEEE 33 node test system with different case studies is considered to validate the performance of HBA. The simulation results of improved voltage profile, minimized power loss, AVDI and improved VSI are tabulated. The proposed HBA fine-tunes the ideal position and size of the EVCSs to significantly enhance RDS performance under higher loading circumstances. To demonstrate the efficacy and originality of the suggested HBA, the numerical results are contrasted with those of earlier soft computing techniques.

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1. INTRODUCTION

More electricity is needed to run India's expanding fleet of electric vehicles (EVs). Other factors contributing to its rising appeal are its better performance, reduced maintenance needs, and low carbon footprint. The rise in EV usage has affected the distribution system's efficiency [1]. The radial distribution system's (RDS) dependability and performance are affected by the placement of the EV charging stations (EVCSs). The fundamental issue is that the RDS is less efficient due to the EVCS's incorrect placement [2]. In general, EVCSs are utilized as loads. Reactive and actual power losses, voltage deviation, voltage profile, and voltage stability index (VSI) minimization all rise proportionately in the distribution system with increasing load.

The allocation problem for EVCSs in RDS has been studied recently, and a number of traditional and soft computing algorithms have been reported. An improved chicken swarm optimization [3] has been applied to optimize the location and size of solar powered EVCSs and lower the power loss and improve voltage at all busses and VSI. A hybrid gray wolf optimization and particle swarm optimization (PSO) [4] was used to allocate the EVCSs and capacitors for lower the power loss in RDS. The same EVCSs and capacitors has been optimized using quantum-behaved and gaussian mutational dragonfly algorithm [5] and simulated results are compared with PSO and biogeography-based optimization (BBO) methods. The EVCSs and distributed generators (DGs) has been used to improve the voltage stability of RDS by combined Harries Hawk optimization and teaching-learning based optimization (TLBO) algorithms [6]. Design and modelling the EVCSs using Monte Carlo simulation method [7] and location and size of EVCSs has been identified by same approach. A traditional EVCSs' charging frequency location was analyzed with any logic technique [8]. The public EV's optimized charging stations enhance the level of sharing charging.

The approach practically identifies the location and size of EVCSs, improves the state of charge (SOC) of EVs. A hybrid chicken swarm optimization and TLBO [9] has been applied to get the Pareto optimal solution of locations and values of EVCSs in RDS. The EVCSs and DGs are optimally allocated using (AI) approach [10] and analyze the reliability of RDS. The AI approach has been based on hybrid grey wolf optimization and PSO and outcomes of power loss, voltage and VSI was displayed. By employing DG and EVCSs based on the V2G mode, an improved harmony PSO [11] was put into place to improve the level of voltage and the net saving of RDS. Through the best possible EVCS allocation, the PSO [12] was used to improve voltage stability in the unbalanced radial distribution system. Utilizing a hybrid genetic algorithm (GA)-PSO [13], plug-in EVCSs and PV-constrained DGs have been allocated to maximize the voltage profile.

A similar problem has been solved using the cuckoo search algorithm with GA [14] and the Levy-enhanced opposition-based gradient-based optimizer [15]. To successfully address the multi-objective optimization issue of finding the ideal position and necessary value of EVCSs, a unique and enhanced version of the honey badger algorithm (HBA) [16] is recommended. Three distinct EVCSs, such as level-1, level-2, and level-3, are allocated optimally using the PSO [17] method that was used. The model has been simulated using open DSS and MATLAB. The most effective way to allocate DSTATCOM and EVCS in the Indian RDS is through the use of the bald eagle search algorithm [18]. For solar-integrated EVCSs, a workable strategy [19] has been established to decrease RDS power loss in urban areas. The method enhances the SOC of EVs and practically locates and sizes EVCSs. The ideal locations of EV-CSs are identified by applying the TLBO algorithm [20], which takes into account the goals of maximizing the VSI and lowering actual power loss and AVDI. To evolve the voltage stability solution in RDS, a fresh and effective meta-heuristic method of group teaching optimization (GTO) algorithm [21] is recommended. Soft open points [22] play an important part in enhancing distribution networks' voltage stability for both normal and fault scenarios. The position and size of multiple distributed generation units can be optimally managed while minimizing the overall active power loss using the PSO with time-varying acceleration coefficients (PSO-TVAC) technique [23].

Finding a solution to the multi-objective optimization voltage stability problem while taking EVCSs and DG units into consideration is the main objective of the current inquiry. The newly created HBA finds the ideal placements and necessary values for DGs and EVCSs. Using a typical IEEE 33-node test system, the method's effectiveness is evaluated. The suggested algorithm examines the EVCSs and DG units using five distinct cases, and the outcomes are contrasted with those of existing soft computing techniques.

2. PROBLEM FORMULATION

The proposed problem solves a multi-objective optimization issue in RDS by taking into account both DGs and EVCSs. The proposed problem's key objectives are to decrease power loss, improve voltage at each bus, and reduce the AVDI and VSI of RDS. To overcome the challenge, an innovative HBA methodology is used:

$$f_1(k) = min \sum_{i=1}^{br} R_i * I_i^2 \tag{1}$$

$$f_2(k) = \frac{1}{b}\sum_{k=1}^{b} |1 - V_k|^2 \tag{2}$$

$$f_3(k) = \left[|V_k|^4 - 4\left(P_k x_{jk} + Q_k r_{jk}\right)^2 - 4\left(P_k r_{jk} + x_{jk}\right)|V_k|^2\right] \tag{3}$$

$$F(k) = \min\left\{w_1 f_1(k) + w_2 f_2(k) + w_3\left(\frac{1}{f_3(k)}\right)\right\} \tag{4}$$

Constraints:

$$\sum_{k=1}^{NG} PG_k - P_L = P_d \tag{5}$$

$$\sum_{k=1}^{NG} QG_k - Q_L = Q_d \quad (6)$$

$$PG_k^{min} \le PG_k \le PG_k^{max} \quad (7)$$

$$0.95 \le V_k \le 1.05, k = 1,2,3, \ldots\ldots, n \quad (8)$$

$$nCP_{min} \le nCP \le nCP_{max} \quad (9)$$

$$nCS_{min} \le nCS \le nCS_{max} \quad (10)$$

In order to reduce power losses, average voltage deviation, and maximize the VSI, the ultimate objective function is generated. Mathematically, this is represented in (4). The power balance constraints of actual and reactive power are represented in (5) and (6). The generator limits of DG units are represented in (7). The voltage limits of each bus are represented in (8). The charging point limit and EV charging station limit constraints are represented in (9) and (10).

3. PROPOSED METHOD

In order to help with the most efficient allocation of EVCSs and DGs in RDS, the current work presented the HBA, a novel and effective metaheuristic optimization approach. Hashim *et al.* [24] generated a proposed algorithm that takes inspiration from the clever foraging behaviour of honey badgers. Due to two distinct phases, known as the honey phase and the digging phase, which are often referred to as the exploration and exploitation phases, HBA has greater seeking ability. For the purpose of solving non-linear, mixed-integer, and complex optimization problems, it is an efficient optimization tool [25], [26].

3.1. Mathematical representation of HBA

Usually, HBA is divided into two distinct stages: digging phase and honey phase. In HBA, the population of potential solutions can be expressed mathematically by,

$$Population\ of\ candidate\ solutions = \begin{bmatrix} x_{11} & x_{12} x_{13} & \ldots x_{1D} \\ x_{21} & x_{22} x_{23} & \ldots x_{2D} \\ & \ldots \ldots \ldots .. & \\ x_{n1} & x_{n2} x_{n3} & \ldots x_{nD} \end{bmatrix} \quad (11)$$

ith position of honey badger,

$$x_i = [x_i^1, x_i^2 \ldots \ldots .. x_i^D] \quad (12)$$

The following steps are considered when addressing non-linear optimization problems:
Step 1: initial setup: begin by initializing the HBA with a population count (N) and their respective positions, calculated using the:

$$x_i = lb_i + r_1 \times (ub_i - lb_i)$$

where the random integer $r1$ is in a range of 0 to 1.
Step 2: intensity calculation: define the intensity, which relates the prey's concentration level to its distance from the honey badger. The strength of the prey's smell is calculated using the inverse square law, as illustrated:

$$I_i = r_2 \times \frac{S}{4\pi d_i^2}$$

where the random integer r_2 is in a range of 0 to 1, $S = (x_i - x_{i+1})^2$ and $d_i = x_{prey} - x_i$.
Step 3: density factor update: the density factor α ensures a balanced transition from exploration to exploitation by regulating time-varying randomness. The decreasing factor α\alphaα, which reduces randomness over time, is updated using the:

$$\alpha = C \times \exp\left(\frac{-t}{t_{max}}\right)$$

where t_{max} is the maximum quantity of iterations and C is a constant (typically C≥1, with a default value of 2).

Step 4: local optima escape: to avoid getting trapped in local optima, this step, along with the following two, is crucial.
Step 5: updating agent positions: in this stage, the positions of the agents are updated. There are two stages to updating an HBA position: the honey phase and the digging phase.

Digging phase: in this phase, the movements of the honey badger mimic those of a cardioid. These movements can be simulated using the following formulas:

$$x_{new} = x_{prey} + \mathrm{F} \times \beta \times I \times x_{prey} + \mathrm{F} \times r_3 \times \propto \times d_i \times |\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \tag{13}$$

$$F = f(x) = \begin{cases} 1, & if r_6 \leq 0.5 \\ -1, & else \end{cases} \quad r_6 \tag{14}$$

is a random integer in the range of 0 and 1.
Honey phase: the scenario that arises when a honey badger follows a honey guide to get to a beehive may be expressed mathematically as,

$$x_{new} = x_{prey} + F \times r_1 \times \alpha \times d_i$$

r_1 is a random integer in the range of 0 and 1.

3.2. Implementation of HBA methodology for allocation of DGs and EVCSs problem

The following steps are applied for solution of MOVSO problem by optimal allocation of EVCSs and DGs using HBA approach:

i) Read the line, bus, load data and features of EVs and CSs of proposed 33 and 69 node test systems.
ii) Run the distribution power flow and calculate the loss using the exact loss formula for the base case.
iii) Fix a number of EVCSs and DGs number of charging points (CPs) and rating charging points that are to be used in the RDS.
iv) Set the population, dimension, top and lower bounds, and maximum quantity of iterations for the HBA.
v) Set the iteration to 1.
vi) Determine the fitness of each digging phase, which includes power loss in a network and the most suitable locations for EVCSs and DGs.
vii) For each digging and honey phase, assess the multi-objective functions.
viii) After updating the locations of the digging and honey phases, store the array's top fitness values.
ix) Compute the present position of digging phase and honey phase.
x) Verify that all constraints have been met; if not, proceed to step 6; otherwise, progress to the next step.
xi) Verify if the quantity of iteration processes matches the maximum quantity of iterations; if so, move on to the next phase. If not, move on to step 5.
xii) When the voltage profile, power loss, AVDI, and VSI global best solution are displayed, the program is stopped.

4. RESULTS AND DISCUSSION

Utilizing the standard IEEE test system 33 node, the applicability and results of the proposed CHBA are evaluated. The test system's line and bus data are obtained from reference [11]. A PC with an i5 Intel Core 4210U processor running at up to 2.5 GHz and 8 GB of RAM memory is used to do the simulations utilizing the MATLAB 14.0 platform. The current research considers battery electric cars (BEVs) and plug-in hybrid EVs (PHEVs) when installing suitable charging places (CPs). Table 1 presents the EV-CSs' design features. The varieties of EVs, their power ratings in kW, the minimum and maximum quantity of charging places, and the charging station ratings in kW are all provided. The charging stations have a minimum power rating of 975 kW and a maximum power rating of 1,674.5 kW, as indicated in Table 1.

Table 1. Simulation-specific attributes of EV and CSs

Type of EV	Power rating of EV (kW)	Quantity of CPs		CS's rating in kW	
		Minimum	Maximum	Minimum	Maximum
Chevrolet volt	2.200	25.00	35.00	55.00	77.00
CHANG AN YIDONG	3.750	20.00	30.00	75.00	112.50
Tesla model X	13.00	15.00	25.00	195.00	325.00
BMW i3	44.00	10.00	20.00	440.00	880.00
SAE J1772 standard	7.00	30.00	40.00	210.00	280.00
The CS's overall power rating (kW)				**975**	**1,674.5**

4.1. Test system 1: 33-node with EVCSs only

First, CHBA's effectiveness and performance are assessed using a typical IEEE-33 node test system. The 33-node network's system and load data are taken from [9]. This test system considers a voltage rating of 12.66 KV and an absolute actual and reactive power load of 3,715 kW and 2,300 KVAr. The population size is 40, the maximum quantity of iterations is 100, and there are seven total variables in the HBA method. The five distinct test cases listed below have been used to examine the proposed system:

- Base case distribution load flow analysis.
- Increasing load demand with minimum number of CPs at minimum power rating all CSs.
- Increasing load demand with maximum number of CPs at maximum power rating all CSs.
- Optimal allocation of EV-CSs using CHBA with minimum number of CPs at minimum power rating all CSs.
- Optimal allocation of EVCSs using CHBA maximum quantity of CPs at maximum power rating all CSs.

Initially, distribution load flow analysis approach is applied and determines the base case voltage of each bus, VSI, minimum VSI, voltage deviation index, minimum voltage and power loss of the network, which is considered as case 1. In case 2, optimally integrate three charging stations connected to sub feeders with a distance of 1 meter each. In this case, consider the minimum number of CPs with the minimum power rating of all CSs. For CSs, at least a power rating of 975 kW is required. Therefore, the load demand is increased to 6,640 kW (3,715+975×3=6,640) by installing the 3 CSs to the sub feeder (load demand is 1.7873 times the base case demand). Now distribution load flow is applied, and the outcomes of the study are displayed in Table 2. It includes a power loss of 576.1705 kW, AVDI of 0.0108, a VSI of 0.4984 (p.u) and a Vmin of 0.8408 (p.u) respectively.

Table 2. Comparing HBA, TLBO, and HHO results for IEEE-33 node test system with EVCSs only

Case	Methods	Locations of EV charging stations	power losses (kW)	AVDI (p.u)	VSI (p.u)	Vmin
Case 1 (base case) load 3,715 kW	-	-	210.9897	0.0040541	0.667174	0.9038
Case 2 load 6,640 kW	-	-	576.1705	0.0108	0.4984	0.8408
Case 3 load 8738	-	-	1024.3908	0.0187	0.3854	0.7888
Case 4	HBA (proposed)	2, 20, 23	281.29	0.0046898	0.651445	0.9010
	TLBO [20]	2, 19, 25	295.6474	0.0047	0.6499	0.8982
	ALO [27]	2, 19, 25	295.6474	0.0047	0.6499	0.8982
	FPA [28]	2, 19, 25	295.6474	0.0047	0.6499	0.8982
	CSA [29]	2, 19, 25	295.6474	0.0047	0.6499	0.8982
	PSO [30]	2, 19, 25	295.6474	0.0047	0.6499	0.8982
Case 5	HBA (proposed)	2, 20, 23	384.5842	0.005121	0.6411	0.9003
	TLBO [20]	2, 19, 25	390.6266	0.0053	0.6381	0.8941
	ALO [27]	2, 19, 25	390.6266	0.0053	0.6381	0.8941
	FPA [28]	2, 19, 25	390.6266	0.0053	0.6381	0.8941
	CSA [29]	2, 19, 25	390.6266	0.0053	0.6381	0.8941
	PSO [30]	2, 19, 25	390.6266	0.0053	0.6381	0.8941
Objective function using HBA (proposed)					**0.82198**	

Similarly, in case 3, consider the maximum number of CPs with the maximum power rating of all CSs. The maximum load of charging stations is 1,674.5 kW, and the total load is 1,674.5×3+3,715=8,738.5 kW (2.3522 times the base case value). The performed load flow analysis and simulation results are projected in the same table. The obtained power loss is 1,024.3908 kW, AVDI is 0.0187, VSI is 0.3854 (p.u) and Vmin is 0.7888 (p.u) respectively. In this case, power loss and AVDI are increased due to maximum load demand. The proposed HBA is applied in cases 2 and 3 and optimally allocates the best location of the charging stations, which are considered in cases 4 and 5. In case 4, considering the total load demand of 6,640 kW and the proposed HBA, optimize the best location of CS with the minimum quantity of CPs. The obtained optimal places are 2, 20 and 23, respectively.

Outcomes of the proposed approach, such as power loss, AVDI, VSI and Vmin are 281.29 kW, 0.0046898 (p.u), 0.651445 (p.u) and 0.9010 (p.u) respectively. Here, power loss is 48.82% reduced compared with case 2 (without optimization). Table 2 presents the simulation results that demonstrate the effectiveness of the suggested HBA approach when compared to TLBO, ALO, PSO, FPA, and CSA techniques. Similarly, in case 5, maximum charging points with a maximum load of 8,738.5 kW are considered to run the distribution load flow with HBA. The HBA effectively tuned the best places of CSs and the best places are 2, 20, 23 respectively. Experimental results of the proposed algorithm, such as power loss, AVDI, VSI and Vmin are 384.5842, 0.005121 (p.u), 0.6411 (p.u) and 0.9003 (p.u) respectively. Here, power loss is 62.44% reduced compared with case 2 (without optimization). The convergence curve for the 33-node system is shown in Figure 1. The lowest, average and highest values of every objective function for the 33-node test system are shown in Table 3. Comparative studies with other optimization algorithms (TLBO, ALO, PSO, FPA and CSA) are considered to verify the superiority of the proposed HBA.

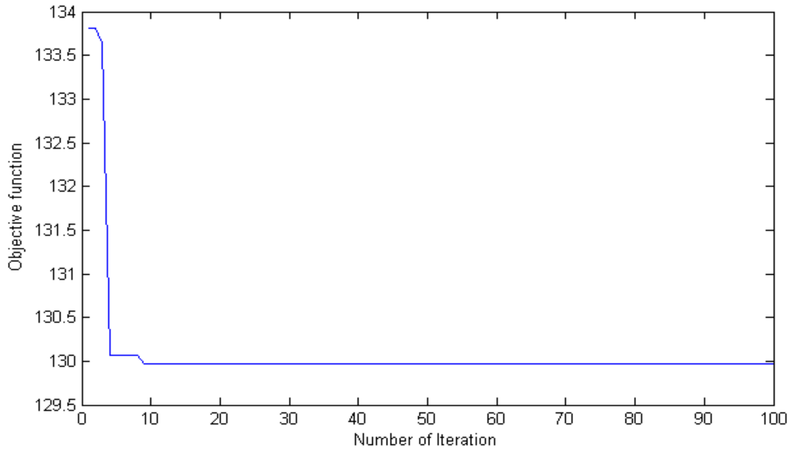

Figure 1. Convergence curve for 33 node test system

Table 3. Comparison of each objective functions for 33 node test system

Values of objective function	power losses (kW)	AVDI (p.u)	VSI (p.u)	Vmin
Case 4: optimal allocation of EVCSs using HBA with minimum number of CPs at minimum power rating all CSs (100 CPs with 975 kW)				
Minimum value	281.29	0.0046898	0.651445	0.9010
Average value	285.3256	0.004712	0.7256	0.9082
Maximum value	290.5786	0.004975	0.9499	0.9982
Case 5: optimal allocation of EVCSs using HBA with maximum number of CPs at maximum power rating all CSs (150 CPs with 1,675 kW)				
Minimum value	384.5842	0.005121	0.6411	0.9003
Average value	387.2314	0.0052347	0.7819	0.9139
Maximum value	389.9546	0.005300	0.9881	0.9954

4.2. Test system 2: 33-node with EVCSs and DG units

This case considers EVCSs and DGs for solution of multi-objective optimization problem. The data of the EVCSs are taken form reference [9] and given in Table 1. The HBA algorithmic specification includes population size=50, maximum iterations=200, total variables=9. The proposed system has been analyzed on the following different test cases:

– Base case distribution load flow analysis.
– Optimal allocation of DGs and EV-CSs using CHBA with minimum number of CPs at minimum power rating all CSs.

Initially, the distribution load flow analysis approach is applied and determines the base case voltage of each bus, VSI, minimum VSI, VDI, minimum voltage and power loss of the proposed network. It considered Case 1 and obtained simulation results, which are given in Table 4. In case 2, considering EVCSs and DGs with a total load demand of 6,640 kW and the suggested HBA optimizes the best placement of CSs and DGs with the minimum quantity of CPs. The obtained optimal locations of DGs and EVCSs are 28, 29, 14 and 2, 19, 25 respectively. The obtained optimal sizes of DGs and EVCSs are 1,500 kW, 793 kW, 1,316 kW and 975 kW, 975 kW, 975 kW respectively. The voltage and VSI at each bus for the base case are only EVCSs and both DGs and EVCSs are compared and numerically reported in Table 4. Additionally, a pictorial comparison is given, as seen in Figures 2 and 3.

Table 4. Comparing HBA, TLBO, and HHO results for IEEE-33 node test system with EVCSs and DG units

Case	Methods	DGs and EV charging station locations	Size of EVCSs and DGs in kW	Power losses (kW)	AVDI (p.u)	VSI (p.u)	Vmin
Case1 (base case)	-	-	-	210.9897	0.0040541	0.667174	0.9038
Case 2	HBA (proposed)	28, 29,14 and 2, 19, 25	1500, 793, 1316 and 975, 975, 975	83.361	0.000436	0.88277	0.9010
	TLBO [6]	13,24,30 and 2, 19, 25	834.61, 1500, 1139.39 and 975, 975, 975	94.3847	0.0047	0.8799	0.9685
	HHO [6]	13,24,30 and 2, 19, 25	837.01, 1500, 1137 and 975, 975, 975	94.3844	0.0047	0.8799	0.9685
Objective function using HBA (proposed)						**0.31099**	

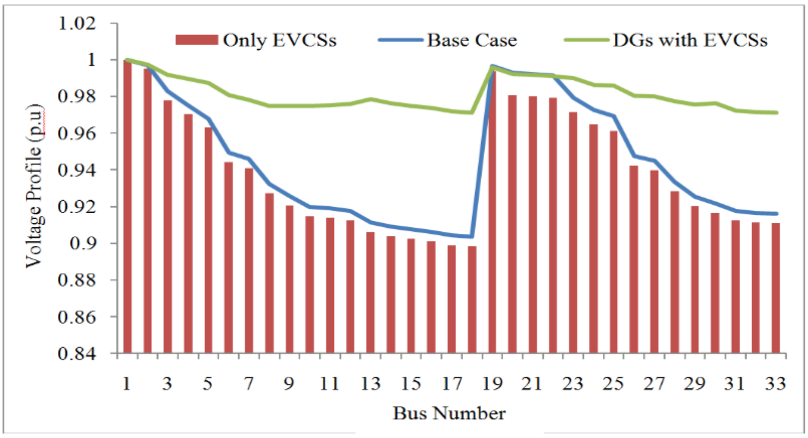

Figure 2. Comparing the voltage profile of the 33-node test setup in the base scenario with only EVCSs and DGs in addition to EVCSs

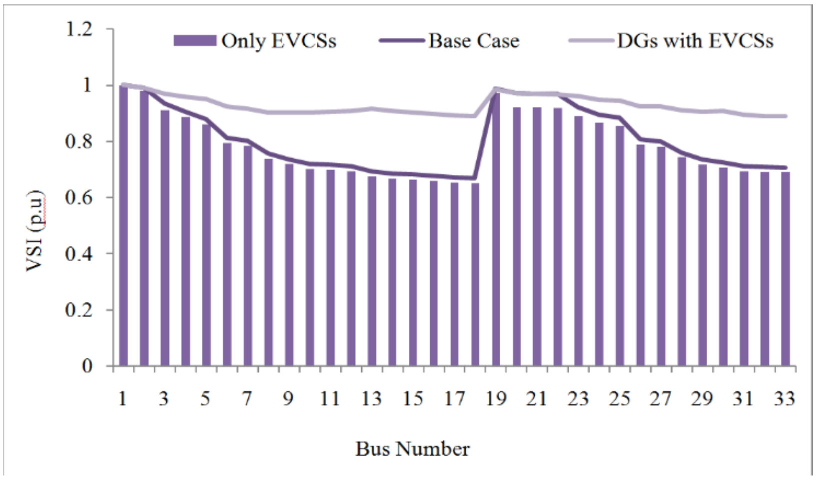

Figure 3. Comparison of the 33-node test system's VSI for the base scenario, with only EVCSs and DGs in along with EVCSs

The outcomes of the proposed approach, such as power loss, AVDI, VSI, and Vmin, are numerically tabulated in Table 4. According to the comparison, the power loss reduction of the suggested test system shows a 60.49% improvement compared to the base case method and a 5.22% improvement over other existing methods like HHO and TLBO. Figure 4 illustrates the convergence characteristics of DGs and EVCSs placement for the IEEE-33 node system. Simulation results, compared with TLBO and HHO techniques, are presented in Table 4 and graphically depicted in Figures 5 and 6. From the comparison, it is evident that the proposed HBA is a powerful and promising technique for solving complex nonlinear optimization problems.

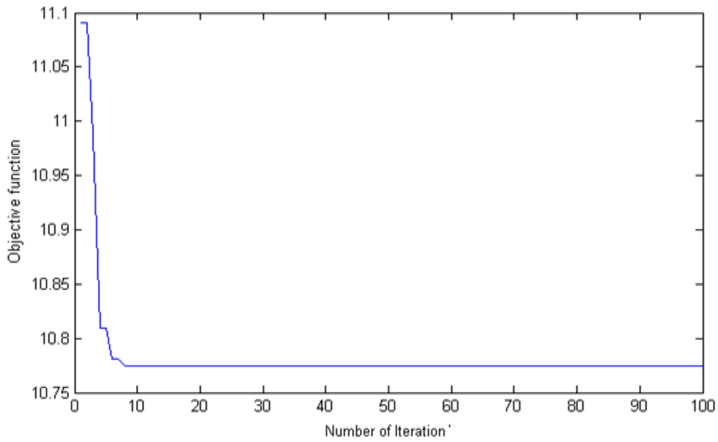

Figure 4. Convergence properties of EVCS placement and DG placement for the IEEE-33 node test system

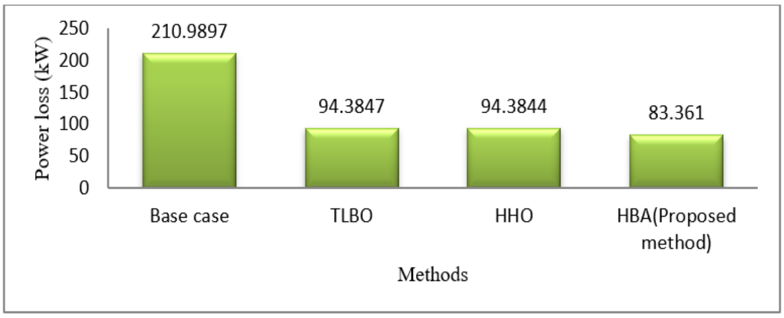

Figure 5. Power loss comparison between the suggested approach and current approaches

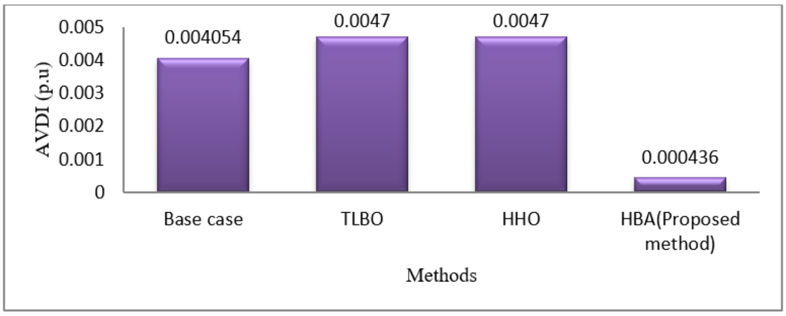

Figure 6. Comparing the suggested method's AVDI with that of the existing techniques

5. CONCLUSION

A novel stochastic search technique based on HBA has been put out to assess the best way to allocate EVCSs and DGs within RDS. The intended HBA effectively determines the ideal placement and necessary values for DGs and EVCSs. In order to compensate for the planned network, the DGs and EVCSs inject and absorb real and reactive power. As a result, VSI and voltage profiles are significantly enhanced. As a result, AVDI and actual and reactive power losses are reduced. The suggested method's simulation results are contrasted with previously published techniques like TLBO and HHO that may be found in the literature.

Based on the comparison, the suggested test system's power loss minimization is 5.22% better than the other HHO and TLBO methods currently in use and 60.49% better than the base case method. The suggested method is new in that it uses a considerably quicker and more reliable convergence of HBA than any other known approach. From the comparison, the applied HBA methodology is the best and most promising optimization technique for solving complex engineering optimization problems. The future scope of the proposed work uses the proposed HBA algorithm to increase the distribution company's profit and the DG owner's advantage in a competitive electricity market.

REFERENCES

[1] T. Yuvaraj *et al.*, "Comparative analysis of various compensating devices in energy trading radial distribution system for voltage regulation and loss mitigation using Blockchain technology and bat algorithm," *Energy Reports*, vol. 7, pp. 8312–8321, Nov. 2021, doi: 10.1016/j.egyr.2021.08.184.

[2] T. Huiling, W. Jiekang, W. Fan, C. Lingmin, L. Zhijun, and Y. Haoran, "An optimization framework for collaborative control of power loss and voltage in distribution systems with DGs and EVs using stochastic fuzzy chance constrained programming," *IEEE Access*, vol. 8, pp. 49013–49027, 2020, doi: 10.1109/ACCESS.2020.2976510.

[3] F. Ahmad, M. Khalid, and B. K. Panigrahi, "An enhanced approach to optimally place the solar powered electric vehicle charging station in distribution network," *Journal of Energy Storage*, vol. 42, p. 103090, Oct. 2021, doi: 10.1016/j.est.2021.103090.

[4] M. Bilal and M. Rizwan, "Integration of electric vehicle charging stations and capacitors in distribution systems with vehicle-to-grid facility," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, pp. 1–30, May 2021, doi: 10.1080/15567036.2021.1923870.

[5] P. Rajesh and F. H. Shajin, "Optimal allocation of EV charging spots and capacitors in distribution network improving voltage and power loss by quantum-behaved and gaussian mutational dragonfly algorithm (QGDA)," *Electric Power Systems Research*, vol. 194, p. 107049, May 2021, doi: 10.1016/j.epsr.2021.107049.

[6] V. K. B. Ponnam and K. Swarnasri, "Multi-objective optimal allocation of electric vehicle charging stations and distributed generators in radial distribution systems using metaheuristic optimization algorithms," *Engineering, Technology & Applied Science Research*, vol. 10, no. 3, pp. 5837–5844, Jun. 2020, doi: 10.48084/etasr.3517.

[7] A. Shahbazi, H. M. C. Beigi, H. Abdi, and M. Shahbazitabar, "Probabilistic optimal allocation of electric vehicle charging stations considering the uncertain loads by using the monte carlo simulation method," *Journal of Operation and Automation in Power Engineering*, vol. 11, no. 4, pp. 277–284, 2023, doi: 10.22098/joape.2023.10427.1738.

[8] D. Gong, M. Tang, B. Buchmeister, and H. Zhang, "Solving location problem for electric vehicle charging stations-a sharing charging model," *IEEE Access*, vol. 7, pp. 138391–138402, 2019, doi: 10.1109/ACCESS.2019.2943079.

[9] S. Deb, K. Tammi, X.-Z. Gao, K. Kalita, and P. Mahanta, "A hybrid multi-objective chicken swarm optimization and teaching learning based algorithm for charging station placement problem," *IEEE Access*, vol. 8, pp. 92573–92590, 2020, doi: 10.1109/ACCESS.2020.2994298.

[10] M. Bilal, M. Rizwan, I. Alsaidan, and F. M. Almasoudi, "AI-based approach for optimal placement of EVCS and DG with reliability analysis," *IEEE Access*, vol. 9, pp. 154204–154224, 2021, doi: 10.1109/ACCESS.2021.3125135.

[11] L. Liu, F. Xie, Z. Huang, and M. Wang, "Multi-objective coordinated optimal allocation of DG and EVCSs based on the V2G mode," *Processes*, vol. 9, no. 1, p. 18, Dec. 2020, doi: 10.3390/pr9010018.

[12] M. S. K. Reddy and K. Selvajyothi, "Optimal placement of electric vehicle charging station for unbalanced radial distribution systems," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, pp. 1–15, Feb. 2020, doi: 10.1080/15567036.2020.1731017.

[13] E. A. Rene, W. S. T. Fokui, and P. K. N. Kouonchie, "Optimal allocation of plug-in electric vehicle charging stations in the distribution network with distributed generation," *Green Energy and Intelligent Transportation*, vol. 2, no. 3, p. 100094, Jun. 2023, doi: 10.1016/j.geits.2023.100094.

[14] K. Yenchamchalit, Y. Kongjeen, P. Prabpal, and K. Bhumkittipich, "Optimal placement of distributed photovoltaic systems and electric vehicle charging stations using metaheuristic optimization techniques," *Symmetry*, vol. 13, no. 12, p. 2378, Dec. 2021, doi: 10.3390/sym13122378.

[15] S. Raval, T. Natarajan, and S. Deb, "A novel levy-enhanced opposition-based gradient-based optimizer (LE-OB-GBO) for charging station placement," *Electronics*, vol. 12, no. 7, p. 1522, Mar. 2023, doi: 10.3390/electronics12071522.

[16] M. Thiruveedula, K. Asokan, and J. B. V Subrahmanyam, "An effective honey badger algorithm based multi-objective optimal allocation of electric vehicle charging stations in radial distribution systems," *Indian Journal Of Science And Technology*, vol. 17, no. 13, pp. 1357–1367, Mar. 2024, doi: 10.17485/IJST/v17i13.3283.

[17] M. Z. Zeb *et al.*, "Optimal placement of electric vehicle charging stations in the active distribution network," *IEEE Access*, vol. 8, pp. 68124–68134, 2020, doi: 10.1109/ACCESS.2020.2984127.

[18] T. Yuvaraj, K. R. Devabalaji, S. B. Thanikanti, V. B. Pamshetti, and N. I. Nwulu, "Integration of electric vehicle charging stations and DSTATCOM in practical indian distribution systems using bald eagle search algorithm," *IEEE Access*, vol. 11, pp. 55149–55168, 2023, doi: 10.1109/ACCESS.2023.3280607.

[19] D. Ji, M. Lv, J. Yang, and W. Yi, "Optimizing the locations and sizes of solar assisted electric vehicle charging stations in an urban area," *IEEE Access*, vol. 8, pp. 112772–112782, 2020, doi: 10.1109/ACCESS.2020.3003071.

[20] P. V. K. Babu and K. Swarnasri, "Multi-objective optimal allocation of electric vehicle charging stations in radial distribution system using teaching learning based optimization," *International Journal of Renewable Energy Research*, vol. 10, no. 1, pp. 366–377, 2020, doi: 10.20508/ijrer.v10i1.10453.g7882.

[21] R. P. Kannemadugu, V. Adhimoorthy, and A. L. Devi, "Optimal allocation of combined DG and DSTATCOM for enhancement of voltage stability in radial distribution networks," *Indian Journal Of Science And Technology*, vol. 16, no. 35, pp. 2845–2855, 2023, doi: 10.17485/ijst/v16i35.1042.

[22] K. Mardanimajd, S. Karimi, and A. Anvari-Moghaddam, "Voltage stability improvement in distribution networks by using soft open points," *International Journal of Electrical Power and Energy Systems*, vol. 155, p. 109582, 2024, doi: 10.1016/j.ijepes.2023.109582.

[23] H. M. Rosli, S. A. Halim, L. J. Awalin, and S. M. Mustaza, "A PSO-TVAC for optimal installation of multiple distributed generations in a radial distribution system," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 32, no. 2, pp. 612–619, 2023, doi: 10.11591/ijeecs.v32.i2.pp612-619.

[24] F. A. Hashim, E. H. Houssein, K. Hussain, M. S. Mabrouk, and W. Al-Atabany, “Honey badger algorithm: new metaheuristic algorithm for solving optimization problems,” *Mathematics and Computers in Simulation*, vol. 192, pp. 84–110, 2022, doi: 10.1016/j.matcom.2021.08.013.
[25] M. A. Elseify, S. Kamel, H. Abdel-Mawgoud, and E. E. Elattar, “A novel approach based on honey badger algorithm for optimal allocation of multiple DG and capacitor in radial distribution networks considering power loss sensitivity,” *Mathematics*, vol. 10, no. 12, p. 2081, Jun. 2022, doi: 10.3390/math10122081.
[26] G. Hu, J. Zhong, and G. Wei, “SaCHBA_PDN: modified honey badger algorithm with multi-strategy for UAV path planning,” *Expert Systems with Applications*, vol. 223, p. 119941, 2023, doi: 10.1016/j.eswa.2023.119941.
[27] H. Zhang and M. Ishikawa, “Characterization of particle swarm optimization with diversive curiosity,” *Neural Computing and Applications*, vol. 18, no. 5, pp. 409–415, 2009, doi: 10.1007/s00521-009-0252-4.
[28] S. Mirjalili, “The ant lion optimizer,” *Advances in Engineering Software*, vol. 83, pp. 80–98, 2015, doi: 10.1016/j.advengsoft.2015.01.010.
[29] X.-S. Yang, “Flower pollination algorithm for global optimization,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 7445 LNCS, 2012, pp. 240–249.
[30] X.-S. Yang and S. Deb, “Engineering optimisation by cuckoo search,” *International Journal of Mathematical Modelling and Numerical Optimisation*, vol. 1, no. 4, pp. 330–343, 2010.

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