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An effective Honey Badger Algorithm based Multi-Objective Optimal Allocation of Electric Vehicle Charging Stations in Radial Distribution Systems

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Abstract

Objectives: To solve the multi-objective optimization problem in Radial Distribution Systems (RDS) using intelligent computational algorithm. The proposed work considers the recently developed Electric Vehicle Charging Stations (EVCSs) to minimize the network loss, reduce the Average Voltage Deviation Index (AVDI) and improve the Voltage Stability Index (VSI) of RDS. **Methods:** A new and novel optimization method of Honey Badger Algorithm (HBA) is proposed to solve the multi objective optimization problem. HBA is divided into two phases such as digging phase and honey phase, which are efficiently determining the optimal location and required value of EVCSs. The MATLAB 14.0 software is sued to implement the HBA methodology. The control parameters HBA such as population size is 40 and number of iteration is 200 iterations **Findings:** The power loss minimization of proposed test system is 48.82% improved when compared with base case method and 2.5 % improved than the other existing methods viz. Particle Swam Optimization (PSO), Flower Pollination Algorithm (FPA), Cuckoo Search Algorithm (CSA) and Teaching Learning Based (TLBO). Similarly, the Average Voltage Deviation Index is 43.42% improved when compared with base case method and 1.2 % improved than the other existing methods. **Novelty:** The proposed HBA effectively improves performance of RDS under increased loading conditions by tuning of the best location and optimal size of the EVCSs.

Keywords: Radial distribution system; Electric Vehicles; Charging Stations; Voltage stability; Power loss and Honey Badger algorithm

1 Introduction

The production and usage of Electric Vehicles (EVs) has been increased recently in India and there is a huge demand for electricity to power the vehicles. As the usage of electric vehicles grows, the distribution systems performance is impacted [1]. The performance and reliability of the Radial Distribution System (RDS) is dependent on the position of the Electric Vehicle Charging Stations (EVCSs). The fundamental difficulty is the deterioration of the RDS due to an incorrect EVCS location [2]. Generally, EVCSs are acted as load. When load increases, corresponding real and reactive power losses of the network are increased, voltage deviation is increased, voltage profile and Voltage Stability Index is minimized.

Recently, researchers documented various classical and soft computing approaches for solution of EVCSs allocation problem in RDS. An improved chicken swarm optimization [3] has been applied to optimize the location and size of solar powered EVCSs and minimize the power loss and improve voltage at all buses and VSI. A hybrid gray wolf optimization and PSO [4] was used to allocate the EVCSs and capacitors for minimization of 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 BBO methods.

The EVCSs and DGs has been used to improve the voltage stability of RDS by combined Harries Hawk Optimization and TLBO algorithms [6]. Design and modeling the EVCSs using Monte Carlo Simulation Method [7] and location and size of EVCSs has been identified by same approach. A classical Any logic approach [8] was applied to analyze the charging frequency location of EVCSs. The optimized charging stations used in a public electric vehicle and improve the sharing charging level.

A practical approach [9] has been developed for solar integrated EVCSs to minimize the power loss of RDS in an Urban Area. The approach practically identifies the location and size of EVCSs, improves the SOC of EVs. A hybrid Chicken Swarm Optimization and TLBO [10] has been applied to obtain the Pareto optimal solution of locations and values of EVCSs in RDS. The EVCSs and DGs are optimally allocated using AI approach [11] 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. An Improved Harmony PSO [12] was implemented to enhance the voltage level and net saving of RDS using DG and EVCSs Based on the V2G Mode

A hybrid bacterial foraging optimization and PSO [13] has been proposed to minimize the real and reactive power of RDS. Here, Rooftop Photovoltaic Systems constrained EVCSs has been considered and it is optimally allocated by a hybrid approach. An improved GA [14] was applied for placement of public CSs by considering the investment of CS operators and the travel costs of BEV owners. The outcome of the work has been minimizing the total cost and emission level of RDS. The PSO [15] was applied to improve the voltage stability in Unbalanced Radial Distribution System by optimal allocation of EVCSs. A hybrid GA-PSO [16] has been used to improve the voltage profile by allocation of both PV constrained DGs and plug-in EVCSs.

The cuckoo search algorithm with GA [17], Levy-enhanced opposition-based gradient based optimizer [18] has been applied to solve the same problem. A hierarchical clustering approach [19] has been applied to solve multi-objective optimal location of EV charging stations in a neighborhood. Ying Zhang et. al developed practical approach [20] and experimental evaluation for optimal placement of EVCSs in RDS. The PSO algorithm [21] was applied and optimally allocates three different EVCSs such as level 1, 2 and 3. The MATLAB and Open DSS have been used to simulate the model. The proposed idea is validated on the real distribution system of the National University of Sciences and Technology (NUST) Pakistan. The Bald Eagle Search Algorithm [22] has been used to find the optimal allocation of DSTATCOM and EVCS in the in Indian RDS.

The non-dominated sorting genetic algorithm-II [23] has been used to determine the best location and size of the EVCSs and distributed energy resources to reduce the power loss of RDS. Genetic algorithm [24] has been applied to minimize the overall cost of deploying the charging network and maximize service quality to users by minimizing the average travel distance between demand spots and stations of RDS. The above methodologies are having own advantages and disadvantages to obtain the optimal solutions.

The scope of this present investigation is to bring out the solution for the multi-objective optimization problem of RDS considering EVCSs. The optimal locations of EVCSs are identified by the novel Honey Badger Algorithm (HBA). The efficiency of the method is tested on standard IEEE 33 and 69 node test systems. The proposed algorithm analyzes the EVCSs with five different cases and obtained results are compared with other soft computing approaches.

2 Methodology

2.1 Proposed Mathematical Formulation

The proposed problem is considered as a multi-objective optimization problem with a view to minimize the power loss and voltage deviation. Further, it improves the voltage profile and voltage stability index of the proposed test system.

2.1.1 Multi-objective function

The proposed multi-objective optimization function is mathematically described as follows

$$MOF = min(w_1 f_1 + w_2 f_2 + w_3(\frac{1}{f_s})) \tag{1}$$

Where,

The real power losses RDS is based on real and reactive power flow of the proposed test system and defined using the Equation (2).

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

The second objective is to minimize the Average Voltage Deviation Index (AVDI) and it is mathematically given in Equation (3).

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

The third objective is to improve the Voltage Stability Index (VSI) of proposed test system and defined as

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

2.1.2 System Constraints

The proposed multi-objective function having followed standard operating constraints and mathematically described as follows

- Voltage limit constraints

$$V_{min} \leq V_i \leq V_{max} \qquad i = 1, 2, ...nb \tag{5}$$

- Total power limit contraints

$$|S_l| \leq |S_{l,max}| \qquad l = 1, 2 \ldots nbl \tag{6}$$

- Charging point limit constraints

$$nCP_{min} \leq nCP \leq nCP_{max} \tag{7}$$

- Charging stations limit constraints

$$nCS_{min} \leq nCS \leq nCS_{max} \tag{8}$$

2.2 Proposed Honey Badger Algorithm (HBA)

This research work proposed a new and effective metaheuristic optimization algorithm called Honey Badger Algorithm (HBA) for optimally allocating EVCSs in RDS. The proposed algorithm inspired from the intelligent foraging behavior of honey badger and developed by Fatma et. al [25]. HBA has more searching ability due to two different phases such as Honey phase and Digging phase and also called exploration and exploitation phases. Therefore, it is powerful optimization tool for solution of Non-linear, mixed integer and complex optimization problems [26,27].

2.3 Mathematical representation of HBA

Generally, HBA is divided into two phases are "digging phase" and "honey phase. The population of candidate solutions in HBA is mathematically defined by

$$Population\ of\ candidate\ solutions\ = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1D} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2D} \\ & \ldots & \ldots & \ldots & . . \\ x_{n1} & x_{n2} & x_{n3} & \cdots & x_{nD} \end{bmatrix} \tag{9}$$

$$i^{th}\ position\ of\ honey\ badger\ x_i\ =\ [x_i^1, x_i^2\ \ldots\ldots.x_i^D] \tag{10}$$

The following steps are considered for solution of non-linear optimization problems

Step 1: Initialization phase

Initialize the population size (N) of the HBA and their respective positions based on Equation (11)

$$x_i\ =\ l\ b_i\ +\ r_1 \times (ub_i - lb_i),\ r_1\ \ is\ a\ random\ number\ between\ 0\ and\ 1 \tag{11}$$

Step 2: Defining Intensity

Intensity is related to concentration strength of the prey and distance between it and i^{th} honey badger. I_i is smell intensity of the prey and mathematically defined by Inverse Square Law which is shown in below equation.

$$I_i\ \ = r_2 \times \frac{S}{4\pi d_i^2},\ r_2\ is\ a\ random\ number\ between\ 0\ and\ 1 \tag{12}$$

Where,

$$S = (\ x_i\ - x_{i+1})^2 \tag{13}$$

$$d_i = x_{prey} - x_i \tag{14}$$

Step 3: Update density factor

The density factor (α) controls time–varying randomization to ensure even transition from exploration to exploitation. Update decreasing factor α that decrease with iterations to decrease randomization with time and mathematically defined by

$$a = C \times exp\left(\frac{-t}{t_{max}}\right),\ t_{max} = maximum\ number\ of\ iterations \tag{15}$$

where C is a constant $\geq$ 1(default = 2).

Step 4: Escaping from local optimum.

This step and the two next steps are very useful for escaping from local optimal solutions.

Step 5: Updating the agents positions

In this step, position of the agents is updated. HBA position update process (x_{new}) is classified into two phases such as digging phase and honey phase.

Digging phase

In digging phase, a honey badger performs action similar to Cardioid shape. The cardioid motion can be simulated by following equations

$$x_{new} =\ x_{prey} + F \times \beta \times I \times x_{prey} + F \times\ r_3 \times\ \propto \times d_i\ \times |cos(2\pi r_4) \times [1 - cos(2\pi r_5)]\,| \tag{16}$$

$$F = f(x) = \begin{cases} 1, & if\ r_6 \leq 0.5 \\ -1, & else \end{cases}\quad r_6\ is\ a\ random\ number\ between\ 0\ and\ 1 \tag{17}$$

Honey phase

The case when a honey badger follows honey guide to reach beehive can be mathematically represented by

$$x_{new}\ =\ x_{prey} +\ F \times\ r_1\ \times\ \alpha\ \times\ d_i,\ r_1\ is\ a\ random\ number\ between\ 0\ and\ 1 \tag{18}$$

In this proposed work, the performance of HBA approach is improved by chaotic mapping. The Chaotic mapping is often used in optimization algorithms to disperse the population and reduce aggregation. The main two classes of chaotic mappings are Logistic chaotic mapping and Tent chaotic mapping, while the latter creates a more uniform chaotic sequence and has a faster convergence speed with more ability to search the exploration and exploitation of the proposed HBA.

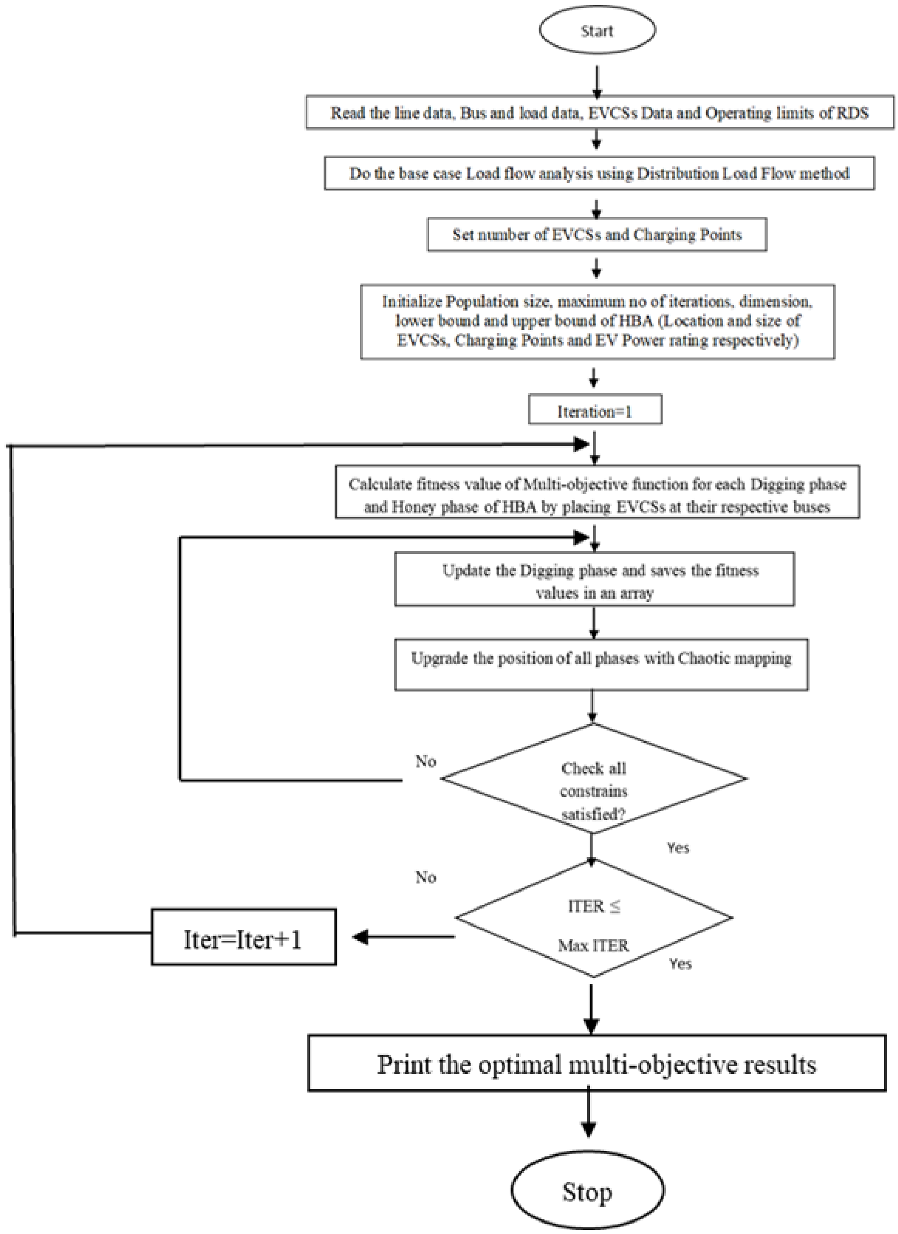

Fig 1. Flow chart of the proposed HBA for optimal allocation of EVCSs

2.4 Implementation of HBA methodology for allocation of EVCSs problem

The following steps are applied for optimal allocation of EVCSs to enhance the voltage profile and reduce the network loss using HBA approach. The flow diagram of proposed HBA for optimal allocation of EVCSs is shown in Figure 1.

1. Read the line, bus, load data and Features of EVs and CSs of proposed 33 and 69 node test systems.
2. Run the distribution power flow and calculate the loss using the exact loss formula for the base case.
3. Fix a number of EVCSs, number of charging points (CPs) and rating charging points that are to be used in the radial distribution system.
4. Initialize the parameters of the HBA such as population, dimension, maximum no of iteration number, lower bound, and upper bound.
5. Set iteration=1.

6. Calculate fitness (i.e., optimal location of EVCSs, power loss in a network) for each digging phase.
7. Evaluate multi-objective functions for each digging phase and honey phase.
8. Update the position of digging phase and honey phase, then save the best fitness values in an array.
9. Compute the present position of digging phase and honey phase.
10. Check it all constraints are satisfied. If yes, move to the next step, or else go back to step 6.
11. Check if the number of iteration processes is equal to a maximum number of iterations. If yes, go to next step. Otherwise, go back to step 5.
12. Display the global best solution of voltage profile, power loss, AVDI and VSI and STOP the program.

3 Results and Discussion

Applicability and outcomes of the proposed CHBA are tested on two standard IEEE test system such as 33 node and 69 node and line data and bus data of the two-test system are taken from reference [12]. The simulations are charred out using MATLAB 14.0 platform, which is implemented on a computer having i5 Intel Core, 4210U processor, up to 2.5 GHz and 8 GB of RAM memory.

Table 1. Features of EV and CSs for the simulation

EV Type	EV power rating (kW)	No. of CPs		Rating of CS (kW)	
		Min	Max	Min	Max
Chevrolet Volt	2.2	25	35	55	77
CHANG AN YIDONG	3.75	20	30	75	112.5
Tesla Model X	13	15	25	195	325
BMW i3	44	10	20	440	880
SAE J1772 Standard	7	30	40	210	280
Total power rating of CS (kW)				**975**	**1674.5**

In the present research work, both Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) are considered for designing the suitable charging Points (CPs). The design features of EV-CSs are displayed in Table 1. It includes types of EVs, power rating of EVs in KW, minimum and maximum number of the charging points, rating of the charging stations in KW. From the Table 1, the minimum and the maximum power rating of the charging stations are 975 KW and 1674.5 KW respectively.

Test system 1: 33-Node Test System

The performance and efficiency of CHBA is initially tested on standard IEEE-33 node test system. The system and load data of the 33-node network is adapted from [10]. The voltage rating is 12.66 KV with an absolute real and reactive power load of 3715 KW and 2300 KVAr are considered in this test system. The HBA algorithmic specification includes population size = 40, maximum iterations = 100, total variables = 7. The proposed system has been analyzed on the following five different test cases.

- 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 EV-CSs using CHBA maximum number 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, integrate three charging stations connected to sub feeders with distance of 1 meter each optimally. In this case, consider minimum number of CPs with minimum power rating of all CSs. The minimum power rating of CSs is 975 kW. Therefore, the load demand is increased to 6640 KW (3715 + 975 x 3 = 6640) by installing the 3 CSs to the sub feeder (load demand is 1.7873 times of base case demand). Now distribution load flow is applied, and outcomes of the study are displayed in Table 2. It includes power loss is 576.1705 KW, AVDI is 0.0108, VSI is 0.4984 (p.u) and Vmin is 0.8408 (p.u) respectively.

Similarly, in case 3, consider maximum number of CPs with maximum power rating of all CSs. Maximum load of charging stations is 1674.5 KW and total load of 1674.5 * 3 + 3715 = 8738.5 KW (2.3522 times of base case value). Performed load flow analysis and simulation results are projected in the same table. The obtained power loss is 1024.3908 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.

Table 2. Simulation results for 33 node test system

Case	Methods	Locations of EV Charging Stations	power losses (KW)	AVDI (p.u)	VSI (p.u)	Vmin
Case 1 (Base Case) Load 3715 kW	-	-	210.9897	0.0040541	0.667174	0.9038
Case 2 Load 6640 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 [28]	2, 19, 25	295.6474	0.0047	0.6499	0.8982
	ALO [29]	2, 19, 25	295.6474	0.0047	0.6499	0.8982
	FPA [30]	2, 19, 25	295.6474	0.0047	0.6499	0.8982
	CSA [31]	2, 19, 25	295.6474	0.0047	0.6499	0.8982
	PSO [32]	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 [28]	2, 19, 25	390.6266	0.0053	0.6381	0.8941
	ALO [29]	2, 19, 25	390.6266	0.0053	0.6381	0.8941
	FPA [30]	2, 19, 25	390.6266	0.0053	0.6381	0.8941
	CSA [31]	2, 19, 25	390.6266	0.0053	0.6381	0.8941
	PSO [32]	2, 19, 25	390.6266	0.0053	0.6381	0.8941
Objective function using HBA (Proposed) 0.82198						

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 975KW)				
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 1675 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

The proposed Honey Badger Algorithm (HBA) is applied in Case 2 and 3 and optimally allocates the best location of the charging stations which are considered as case 4 and case 5. In case 4, considering the total load demand of 6640 KW and proposed HBO optimize the best location of CS with minimum number of CPs. The obtained optimal locations 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). The simulation results are compared with TLBO, ALO, PSO, FPA and CSA techniques and are given in Table 2 to prove the performance of the proposed HBA algorithm.

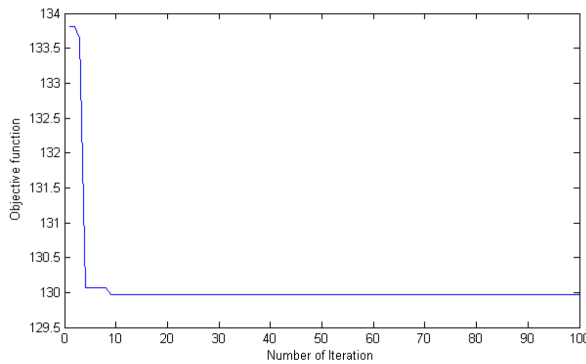

Fig 2. Convergence curve for 33 node test system

Similarly, in case 5, maximum charging points with maximum load of 8738.5 KW are considered to run the distribution load flow with HBA. The HBA effectively tuning the best location of CSs and best locations are 2, 20, 23 respectively. Experimental results of the proposed algorithm such as power loss, AVDI, VSI and Vmin is 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). Convergence curve for 33 node test system is shown in Figure 2. The minimum, average and maximum values of each objective function for 33 node test system are shown in Table 3. Comparative study with other optimization algorithm of TLBO, ALO, PSO, FPA and CSA are considered to verify the superiority of the proposed HBA.

Test case 2: 69 Node test system

In order to validate the ability of the proposed CHBA algorithm, a large scale 69 bus test system is examined to achieve global optimal solutions. Generally, the projected test system has the operating voltage of 12.66 kV with the real and reactive power load of 3801.4 kW and 2693.6 kVAr respectively. The distribution load flow is applied and finds the minimum voltage, real and reactive power loss of 69- node test system. The outcomes of the minimum voltage, real and reactive power losses are 0.9092 p.u, 224.8807 kW and 102.1094 kVAr respectively. The CHBA contains only conmen control parameters like population size = 50, Maximum iterations = 200, total variables = 7. The proposed system is analyzed using five different test cases similar to the 33-node test system.

Table 4. Simulation results for 69 node test system

Case	Methods	Locations of EV Charging Stations	power losses (KW)	AVDI (p.u)	VSI (p.u)	Vmin
Case 1 (Base Case) Load 3801.4 kW	-		224.97	0.0014393	0.683323	0.9092
Case 2 Load 6640	-		613.4994	0.004	0.5114	0.8462
Case 3 Load 8738 kW			1108.6266	0.0072	0.3949	0.7935
Case 4	**HBA (proposed)**	**2 28 3**	**225.1700**	**0.0014402**	**0.683274**	**0.9092**
	TLBO [28]	2, 28, 47	225.2186	0.0014	0.6822	0.9092
	ALO [29]	2, 28, 47	225.2186	0.0014	0.6822	0.9092
	FPA [30]	2, 28, 47	225.2186	0.0014	0.6822	0.9092
	CSA [31]	2, 28, 47	225.2186	0.0014	0.6822	0.9092
	PSO [32]	2, 28, 47	225.2186	0.0014	0.6822	0.9092
Case 5	**HBA (proposed)**	**2 28 3**	**225.4122**	**0.0014493**	**0.683052**	**0.9092**

Continued on next page

Table 4 continued

TLBO [28]	2, 28, 47	225.5766	0.0014	0.6821	0.9092
ALO [29]	2, 28, 47	225.5766	0.0014	0.6821	0.9092
FPA [30]	2, 28, 47	225.5766	0.0014	0.6821	0.9092
CSA [31]	2, 28, 47	225.5766	0.0014	0.6821	0.9092
PSO [32]	2, 28, 47	225.5766	0.0014	0.6821	0.9092
Objective function using HBA (Proposed) 0.64736					

Table 5. Comparison of each objective functions for 69 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 975KW)				
Minimum Value	225.1700	0.0014402	0.683274	0.9092
Average Value	226.7824	0.0014586	0.78362	0.9375
Maximum Value	227.5432	0.0014926	0.96022	0.9662
Case 5: Optimal allocation of EVCSs using HBA with maximum number of CPs at maximum power rating all CSs (150 CPs with 1675 KW)				
Minimum Value	225.5766	0.0014000	0.6821	0.9092
Average Value	226.8912	0.0014011	0.7865	0.9254
Maximum Value	227.4812	0.0014210	0.9836	0.9576

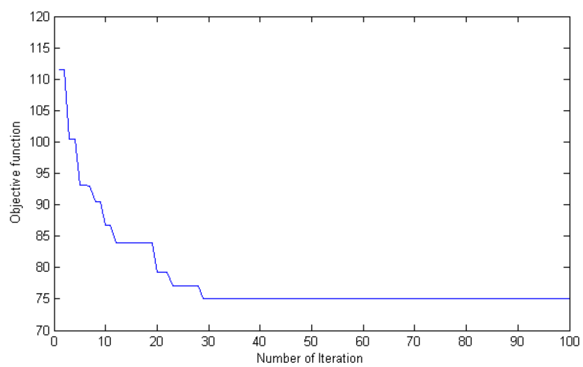

Fig 3. Convergence curve for 69 node test system

The simulation results of without optimizations (case 1, case 2 and case 3) are displayed in Table 4. This table includes real power loss KW), AVDI (p.u), VSI (p.u) and Vmin. In case 4 and case 5, the proposed CHBA is applied to find out the optimal location of the three CSs. The optimal location of three CSs in case 4 and case 5 are 2, 28, 3 respectively. The power loss of case 4 and case 5 is 225.1700 KW and 225.4122 KW also displayed in Table 4. This power loss in cases 4 and 5 is effectively minimized when compared with case 2 and 3 (without optimization). Convergence curve for 69 node test system is shown in Figure 3. Finally, simulation results of case 4 and case 5 are compared with other available methods of TLBO, ALO, PSO, FPA, CSA and shown in Table 4. The minimum, average and maximum values of each objective function for 69 node test system are shown in Table 5. The projected CHBA efficiently minimizes the power loss and AVDI loss and improves the voltage profile and VSI of the proposed test system.

4 Conclusion

A novel Honey Badger algorithm (HBA) has been proposed for the evaluation of optimal allocation of Electric Vehicle Charging Stations (EVCSs) in the radial distribution systems (RDS). The proposed method achieved, the power loss minimization of 48.82% when compared with base case method and 2.5 % improved than the other existing methods of PSO, FPA, CSA and TLBO. Similarly, the Average Voltage Deviation Index is 43.42% improved when compared with base case method and 1.2 %

improved than the other existing methods. The novelty of the proposed work is that the convergence of HBA is much faster and more reliable than the other existing approaches. When compared to the existing methods PSO, FPA, CSA and TLBO, the applied HBA methodology is one the best and promising optimization technique for solving complex engineering optimization problems. The future scope of the proposed work is DGs and FACTS devices are interconnected with EVCSs to effectively reduce the power loss and improve the voltage stability of RDS using a proposed HBA algorithm.

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