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Honey Badger Algorithm Based Network Reconfiguration and Integration of Renewable Distributed Generation for Electric Vehicles Load Penetration

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Abstract: Several studies in the literature have focused the use of optimum network reconfiguration (ONR) and/or optimal allocation of renewable energy (RE) based distributed generation (DG) methodologies to improve performance in electrical distribution networks (EDNs). However, a few studies have only focused at simultaneous ONR and DG allocation in the context of demand increase, network loading unpredictability, or RE power. Furthermore, there is no much focus on the influence of emerging electric vehicle (EV) load penetration on EDN performance. This study proposes a novel meta-heuristic strategy for solving the simultaneous optimal ONR and RE-based DGs allocation problem for minimising distribution losses, improving voltage profile, and lowering greenhouse gas (GHG) emissions while considering the load penetration of electric vehicles (EVs). For solving the complexity inherent in the multi-objective optimization problem with numerous constraints and multi-type variables, a new and efficient honey badger algorithm (HBA) is proposed. On the IEEE 33-bus EDN, simulations are run with various EV load penetration levels. In terms of fitness function, HBA is observed to be superior to COA, TLBO, CSA, and PSO. As observed in the results, for 50% EV load penetration, the losses, AVD, and GHG emissions are increased to 1571.676 kW, 0.02658 p.u., and 25780.05 103 (lb/h), respectively. However, by having DGs optimally and with ONR, the losses, AVD, and GHG emissions are decreased to 77.08 kW, 0.00038 p.u., and 2175.01103 (lb/h), respectively. This indicates that the performance of EDN is improved significantly by having simultaneous DGs allocation and ONR solution irrespective of EV load penetration level. This also indicates the suitability of the proposed methodology for practical applications.

Keywords: Distributed generation, Electrical distribution networks, Electric vehicles, Honey badger algorithm, Network reconfiguration, Renewable energy.

1. Introduction

Majority of the electrical distribution networks (EDNs) are radial in configuration and designed with high R/X ratio distribution lines, which causes to operate at low voltage profile, increased distribution losses and reduced stability margins. Also, continuously increasing demand for electricity and expanding network size makes this situation more severe. On the other hand, increasing global warming, diminishing fuel sources and increasing fuel cost, balancing electricity demand using conventional power sources become nonviable in terms of both economic and environmental point of view. Thus, many countries are transforming their power generation strategy towards renewable energy (RE) and transportation systems towards electric vehicles (EVs). Though this transition is inevitable for sustainability point of view, both RE and EV technologies have opened up various challenging operational and controlling issues due to their stochastic and random nature. In order to attain techno-economic benefits along with environmental benefits, there is need for optimization strategy for coordinating these two technologies.

In EDNs, integration of distributed generation (DG), network reconfiguration (NR) and allocation of EV charging stations (EVCS) are considered as optimization strategies at planning stages. However, their control in a cooperative approach becomes very essential for an effective operation irrespective of level of variability in both generation and network loading. Optimal network reconfiguration (ONR) is one such optimal control strategy employed for managing network loading conditions due to randomness in both generation and loads. In a network with ns-switches (where $ns = nbr + ntl$, nbr-branches and ntl-tie lines), the possible configurations are 2^{ns}. As ns increase, the number of combinations will increase and correspondingly computational time may increase significantly. At this stage, ONR is said to be non-linear optimization problem with discrete search variables for identifying optimal switches to alter their on/off state.

Similarly, optimal allocation of DGs (OADG) is essential planning strategy to attain techno-economic-environmental goals. However, OADG problem needs to be solved for identification of DG locations as discrete search variables in the range of $[2, nbus]_{(1\times ndg)}$ (where $nbus$ is number of buses and ndg is number of DGs) and evaluation of DG sizes as continuous search variables in the range of $[2, P_D]_{(1\times ndg)}$ (where P_D is total network real power load). At this stage, OADG problem is said to be multi-variable optimization problem and its complexity may further increase as search space increases in proportion to increase in ndg and/or $nbus$. On the other hand, simultaneous ONR and OADG problem can be considered as non-linear multi-variable complex optimization problem. Thus, in literature, many heuristic approaches are proposed for solving ONR and/or OADG problems.

In [1], a modified selective particle swarm optimization (SPSO) is proposed for ONR problem considering real and reactive power distribution losses and voltage profile improvement as multi-objective functions. Simulations are performed on IEEE 33-bus EDN considering light, normal and heavy loading conditions. Considering distribution losses, annual cost and greenhouse gas (GHG) emission, a multi-objective function is minimized in solving simultaneous ONR and OADG problems using Strength Pareto Evolutionary Algorithm 2 (SPEA2) [2]. In [3], coyote optimization algorithm (COA) is introduced for loss minimization. In [4], water cycle algorithm (WCA) is implemented for simultaneous ONR and OADG along with optimal control of DGs' power factor towards distribution loss minimization. In [5], a comparative study of different heuristic approaches namely particle swarm optimization (PSO), genetic algorithm (GA), differential evaluation (DE) and ant colony optimization (ACO) is presented for solving ONR and OADG problem simultaneously towards loss reduction. In [6], DG hosting capacity (HC) and voltage profile are aimed to increase whereas the losses are aimed to decrease in simultaneous OADG and ONR problem using switch opening exchange (SOE) method and success history based adaptive differential evolution algorithm (SHADE). In [7], comprehensive teaching-learning based optimisation (CTLBO) algorithm is proposed for loadability enhancement while solving simultaneous ONR and OADG problems. In [8], comprehensive teaching learning harmony search optimization algorithm (CTLHSO) is developed by hybridizing TLBO and (HS) for solving OADG and ONR problems towards loss reduction. A new chaotic search group algorithm (CSGA) is introduced for OADG and ONR problems for loss minimization under different loading conditions [9]. Artificial immune bee colony (AIBC) optimization [10], an enhanced sine–cosine algorithm (ESCA) [11], analytical approach [12], improved particle swarm optimization (IPSO) [13], artificial bee colony (ABC) [14], hybrid approach HS-PABC using harmony search algorithm (HSA) and particle artificial bee colony algorithm (PABC) [15], exact loss formula based heuristic approach [16], imperialist competitive algorithm (ICA) [17], bacterial foraging optimization (BFO) with fuzzy sets [18] are proposed for solving simultaneous ONR and OADG problems. In [19], harmony search algorithm (HAS) is introduced for solving simultaneous NR and DG allocation problem. Loss sensitivity factors (LSFs) are used to reduce the search space of DGs and the problem is solved for loss minimization.

According to these studies, combining ONR and OADG can result in more substantial and efficient EDN operation. Given the considerable uncertainty that current EDNs face as a result of RE generation and EV loads, this paper focuses on a simultaneous method for achieving combined benefits. Further, different heuristic approaches and their comparison can be seen in the comprehensive review presented in [20]. However, majority of the algorithms are suffering with slow convergence and local optima trap. To overcome this, researchers are highly inspiring to introduce simple and efficient algorithms and also focused on either hybridization of basic algorithms or modifications at either exploration or exploitation phases. In this line, honey badger algorithm (HBA), is a recent meta-heuristic and efficient nature-inspired method, and its computational efficiency have been demonstrated using a variety of heuristic techniques to solve a variety of benchmark optimization problems [21].

In light of the above literature, the following are the major contributions of this paper.

1) Multi-objective optimization problem for simultaneous allocation of DGs and ONR is proposed.
2) For the first time, HBA is introduced to solve the simultaneous ONR and OADG problem, which has good exploration and exploitation characteristics.
3) Loss minimization, voltage profile improvement and GHG emission reduction are considered while formulating multi-objective function.
4) In contrast to the literature, the simulations are also extended by considering emerging EV load penetration levels.
5) The computational efficiency of HBA is compared based on simulations on IEEE 33-bus EDN with COA, TLBO, CSA and PSO.

Rest of the paper is organised as follows: Section 2 explains mathematical modelling of EV load and RE-based DGs suitably for load flow studies. Section 3 gives the proposed multi-objective optimization problem. Section 4 explains the concept o HBA and its implementation procedure for solving the proposed optimization problem. Section 5 explains the results of obtained by HBA for different scenarios in IEEE 33-bus EDN. Section 6 concludes the major contribution and novelty of this paper.

2. Modelling of relevant concepts

In this section, modelling of EV load penetration and RE-based DGs are explained considering the steady-state load flow equations of power system.

2.1 Electric vehicles load penetration

In general, EVs can be connected to the EDN via AC/DC charger. The real power demand due to EVs is dependent on type, number and their state of charge (SoC) levels. Also, the reactive power demand by EVs is dependent of operating power factor AC/DC converter. Thus, the additional real and reactive power loads due to EVs are expressed using voltage-dependent load modelling, as follows [22]:

$$P_{d(i)} = P_{d0(i)} + P_{d,ev(i)} \left(\frac{|V_{(i)}|}{|V_{(s)}|}\right)^{\alpha} \tag{1}$$

$$Q_{d(i)} = Q_{d0(i)} + P_{d,ev(i)} \tan(\emptyset_{(k)}) \left(\frac{|V_{(i)}|}{|V_{(s)}|}\right)^{\beta} \tag{2}$$

$$P_{d,ev(i)} = \lambda_{pen} P_{d0(i)} \tag{3}$$

where $P_{d0(i)}$ and $Q_{d0(i)}$ are the base case real and reactive power loads, respectively; $P_{d(i)}$ and $Q_{d(i)}$ are the real and reactive power loads of bus-*i* after integration of EVs, respectively;$P_{d,ev(i)}$ is the total EV load at bus-*i*, $P_{ev(k)}$ and λ_{pen} are the *k*th EV power rating and EV penetration level (i.e., battery SoC level), respectively; $\emptyset_{(k)}$ is the power factor angle of *k*th EV charger, $|V_{(i)}|$ and $|V_{(s)}|$ are the voltage magnitudes of bus-*i* and sub-station bus-*s*, respectively; α and β are the exponential coefficients for battery charging loads as per voltage dependent load modelling, respectively;$nev$is the number of EVs connected at bus-*i*.

2.2 Renewable distributed generation

Distributed generation (DG) is a concept of power generation at consumer’s site and its range can be a few kW to MW. However, RE type DGs can be possible to connect EDN via DC/AC or AC/AC type power converters for grid compatibility. Thus, the operating power of converter can result for reactive power output from DGs. Considering these aspects, the real and reactive power generations by DGs can be offset from the actual load at which it is integrated. The following model is presented to obtain net load at a bus after DG integration.

$$P_{d(i)} = P_{d0(i)} - P_{dg(i)} \tag{4}$$

$$Q_{d(i)} = Q_{d0(i)} - P_{dg(i)} tan(\emptyset_{(i)}) \tag{5}$$

where $P_{g,dg(i)}$ and $\emptyset_{(i)}$ are the real power generation by a DG at bus-*i* and its operating power factor, respectively.

For photovoltaic (PV) type DG, the power is to be ideal and thus, reactive power support by PV type DGs can become zero. On the other hand, wind turbine (WT) type DGs are capable to operate at a fixed power factor and adjustable power factor. Thus, WT type DGs can support both real and reactive powers to the EDN.

3. Problem formulation

In this work, a multi-objective function (OF) using real power losses (P_{loss}), average voltage deviation (AVD) and greenhouse gas (GHG) emission (GHG_{grid}) is formulated for simultaneous NR and DG allocation problem considering EV load penetration and optimized using HBA.

$$OF = P_{loss} + AVD + GHG_{grid} \quad (6)$$

$$P_{loss} = \sum_{k=1}^{nbr} I_k^2 r_k \quad (7)$$

$$AVD = \frac{1}{nbus}\sum_{i=1}^{nbus} abs(1 - |V_i|) \quad (8)$$

$$GHG_{grid} = P_{grid} \times (CO_2 + SO_2 + NO_x) \quad (9)$$

where r_k and I_k are the resistance and current through branch-k, respectively; $nbus$ is the number of buses in the network, $|V_i|$ is the voltage magnitude of bus-*i*, P_{grid} is the extracting power by EDN from main grid, CO_2, SO_2 and NO_x are the pollutants from conventional power plants associated with main grid, respectively.

The following are the operational and planning constraints considered in this work. Eqs. (10) and (11) describe the real and reactive power balances, respectively; Eqs. (12) and (13) describe the real and reactive power generation limits for DGs, respectively; Eqs. (14) and (15) describe the DG size limits for real and reactive powers, respectively; Eq. (16) describes bus voltage magnitude limit, Eq. (17) describes branch current limit, and Eq. (18) describes radiality constraint.

$$P_{grid} = P_{loss} + \sum_{i=1}^{nbus} P_{d(i)} \quad (10)$$

$$Q_{grid} = Q_{loss} + \sum_{i=1}^{nbus} Q_{d(i)} \quad (11)$$

$$\sum_{i=1}^{nbus} P_{dg(i)} \leq \sum_{i=1}^{nbus} P_{d0(i)} + \sum_{i=1}^{nbus} P_{d,ev(i)} \quad (12)$$

$$\sum_{i=1}^{nbus} Q_{dg(i)} \leq \sum_{i=1}^{nbus} Q_{d0(i)} + \sum_{i=1}^{nbus} Q_{d,ev(i)} \quad (13)$$

$$P_{dg,min} \leq P_{dg} \leq P_{dg,max} \quad (14)$$

$$Q_{dg,min} \leq Q_{dg} \leq Q_{dg,max} \quad (15)$$

$$|V_i|_{min} \leq |V_i| \leq |V_i|_{max} \quad (16)$$

$$I_k \leq I_{k,max} \quad (17)$$

$$nbr = nbus - 1 \text{ and } |\bar{A}| = 0 \quad (18)$$

where Q_{grid} and Q_{loss} are the extracted reactive power from the main grid and reactive power losses, respectively; $|V_i|_{min}$ and $|V_i|_{max}$ are the minimum and maximum voltage limits of bus-*i*, respectively; $I_{k,max}$ is the maximum branch current limit, nbr is the number of branches in the EDN, $|\bar{A}|$ is det of element-bus incident matrix.

4. Honey badger algorithm

One of such recent algorithms, honey badger algorithm (HBA), introduced by Fatma A. Hashim et al. in 2022 [21], is so simple and easy to implement by having a small number of parameters and works efficiently as compared with similar type of algorithms. A honey badger hunts its prey by strolling slowly and using its mouse senses. It burrows through the dirt to find its prey, then catches it. It can dig up to 50 holes a day, each at least 40 km apart, in quest of food. Bee hives are hard to find for this animal who loves honey. A honey-guide (bird) can find the hives but not get the honey. Birds and badgers find beehives together. In the beehives, it guides the badger with its long claws. By mimicking the food searching behaviour honey badger, HBA is developed as global optimization algorithm. The honey badger either smells and digs for food and later follows the honey guide bird. These two specific features are used in HBA and termed as digging phase and honey phase, respectively

4.1 Mathematical modeling of HBA

In similar to all kinds of swarm-based algorithms, HBA also starts with an initialization of random population, mathematically,

$$x_{ij} = l_{ij} + r_1 \times \left(u_{ij} - l_{ij}\right) \quad (19)$$

where $i = 1{:}N \& j = 1{:}D$, l_{ij} and u_{ij} are the are the lower and upper limits of the search space, respectively; r_1 is uniformly distributed random number between 0 and 1, x_{ij} is the position of *i*th candidate/ honey badger, $N$and$D$ are the number of population and dimension of search space, respectively.

The motion of honey badger is dependent on the smell intensity of the food source. Intensity (I_i) is determined by the prey's concentration strength and the distance between it and the honey badger. Using Inverse Square Law, it is modelled by,

$$I_i = r_2 \times \frac{C}{4\pi d_i^2} \quad (20)$$

where C is the prey location or concentration strength given by $(x_i - x_{i+1})^2$, r_2 is the random number between 0 and 1, $d_i = \left(x_p - x_i\right)$ is the distance between food source (x_p) and the ith honey badger (x_i).

A decreasing density factor is defined to guarantee a seamless transition from exploration to exploitation, as well as to manage time-varying randomness in the overall process.

$$\alpha = K \times exp\left(\frac{-t}{T}\right), K \geq 1 \tag{21}$$

where t and T are the current iteration and maximum number of iterations, respectively; K is a constant and by default, it is equal to 2.

By avoiding local trap occurrences, the honey badger's position is updated. In HBA, a flag F is used for this, by which the search direction can be changed to favour high chances for candidates to thoroughly explore the search space. As mentioned at the beginning, HBA follows two phases for updating position of the honey badgers.

4.1.1. Digging phase

During digging phase, the position of honey badger is updated,

$$x_n = x_p + F \times \beta \times I \times x_p + F \times r_3 \times \alpha \times d_i \times |\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \tag{22}$$

where x_p is the best position of the prey determined so far, $\beta \geq 1$ is defined as the ability of honey badger to find food and its default value is 6, F is the flag to alter search direction, defined by,

$$F = \begin{cases} +1 & if\ r_6 \leq 0 \\ -1 & else \end{cases} \tag{23}$$

A honey badger's digging phase is highly influenced by the smell intensity I of prey x_p, the distance between the badger and prey d_i, and the time-varying search influence factor α. Additionally, while digging, a badger may encounter any disruption F, allowing it to locate even greater prey.

4.1.2. Honey phase

To imitate the situation in which a honey badger follows a honey guide bird to reach a beehive is modelled as honey phase in HBA.

$$x_n = x_p + F \times r_7 \times \alpha \times d_i \tag{24}$$

where r_3, r_4, r_5, r_6 and r_7 are the random numbers between 0 and 1.

From Eq. (24), it can be seen that a honey badger searches for prey close to the prey site x_p that has been discovered thus far, based on distance information d_i. At this step, the search is influenced by time-varying search behaviour (α). Additionally, a honey badger may discover disruption F.

4.2 Solution methodology

The following are the major steps involved for allocating DGs and ONR simultaneously.

St 1. Define EV load penetration level and solve base case condition using NR method.

St 2. Repeat NR load flow by considering each load bus as a generator bus at a time, and store the locations for which NR method converges. This stage provides the reduced search space for DGs location.

St 3. Close all tie-lines and convert radial to mesh network. Perform load flow and determine objective function.

St 4. Define number of DGs to be installed in the network and correspondingly population, dimension, and also maximum iterations.

St 5. Generate random locations and sizes (i.e., total real power generation of DGs should be less than or equal to network real power demand and total reactive power of DGs should be equal to network reactive power demand). Generate random search space of switches for transforming mesh to radial network.

St 6. Evaluate fitness of each population and determine best population and fitness function value.

St 7. Perform digging phase and honey phase for updating the position of population and correspondingly fitness function value.

St 8. Evaluate new positions and their fitness and return best if convergence criterion satisfies.

St 9. Compare network performance matrices for base case and optimal solution of HBA and print report.

5. Results and discussion

The computational efficiency of proposed HBA is evaluated by simulating different case studies on IEEE 33-bus EDN [22]. It has 33 buses, 32 branches (normally ON) and 5 tie-lines (normally open OFF). The network is serving totally real and reactive power loads of 3715 kW and 2300 kVAr, respectively. For basic radial configuration, it has real and reactive power losses of 202.6771 kW and 135.141 kVAr, respectively. The minimum voltage magnitude of 0.9138 p.u. is recorded at bus-18. The voltage deviation index (VDI) is estimated as 0.0515 p.u. Since the overall network load is serving by main grid, by assuming generation by conventional power sources, the GHG emission is estimated as 8022.07 lb/h.

5.1 Solution for only ONR problem

In this section, the results of HBA in solving only the ONR problem are presented and compared with the literature. Later, ONR is solved for different EV load penetrations. In addition, only loss reduction and voltage profile improvement are considered since ONR may not contribute to the reduction of GHG emissions in EDNs. The best results obtained by HBA are discussed here. The optimal branches open (OFF) are 7, 9, 14, and 32, and the closed tie-line (ON) is only 37. With this optimised configuration, the network has reduced real and reactive power losses to 139.5513 kW and 102.305 kVAr, respectively. The minimum voltage magnitude of 0.9378 p.u. is recorded at bus-32. The voltage deviation index (VDI) is estimated at 0.0348 p.u. The GHG emission is estimated to be 7892.811 lb/h if conventional power sources are used.

The results of HBA are compared with literature and the results are given in Table 1. From this, HBA can be seen as a competitive algorithm in solving the ONR problem. From this, the network performance is significantly improved with reduced losses and an improved voltage profile. According to [23, 24], the global solution for this IEEE 33-bus standard test system, is comparable to the results produced by CTLHSO [8], ESCA [11], DS [16], ICA [17], and the proposed HBA. However, this global solution gives lesser/higher values to SPSO [1], BFO [18], and HAS [19], which is due to either an erroneous fundamental load flow solution or their premature convergence characteristics.

Table 1. HBA results for only ONR problem

Method	**Open Switches**	**P_{loss} (kW)**
Base	33, 34, 35, 36, 37	202.6771
SPSO [1]	7, 11, 28, 32, 34	112.58
BFO [18]	7, 9, 14, 31, 37	132.69
AIBC [10]	7, 9, 14, 31, 37	142.61
HAS [19]	7, 9, 14, 32, 37	138.06
CTLHSO [8]	7, 9, 14, 32, 37	139.5513
ESCA [11]	7, 9, 14, 32, 37	139.5513
DS [16]	7, 9, 14, 32, 37	139.5513
ICA [17]	7, 9, 14, 32, 37	139.5513
HBA	7, 9, 14, 32, 37	**139.5513**

5.2 Solution for simultaneous ONR and OADG problems

In this, simultaneous ONR and OADG problems are solved using HBA and compared with earlier literature works. Since the DGs are locally generating power, the burden on the main-grid can decrease, which results in a reduction in GHG emissions. The proposed multi-objective expressed in Eq. (6) is optimised and the results are given in Table 2. In addition, different methods used in the literature were also compared. It can be seen that the HBA provided the best results over COA [2], WCA [4], CTLHSO [8], SGA [9], CSGA [9], ESCA [11], DS [16], ICA [17], BFO [18], and HAS [19]. Most of these works are limited their search space by using loss sensitivity factors (LSFs) and VSI based predefined search space and thus resulted for non-global optima. In addition, erroneous fundamental load flow solution is another reason for resulting lesser/higher solution than global solution.

The optimised results of HBA are as follows: The open switches are: 11, 28, 31, 33, and 34. The DG sizes in kW and their locations are: 752.5 (17), 956.8 (7), and 1280.34 (25). This results in a reduction in real and reactive power losses of 50.718 kW and 38.721 kVAr, respectively. The minimum voltage is observed as 0.9734 p.u. at bus-32, and the VDI is estimated as 0.00024 p.u. Also, the GHG emissions are reduced to 1588.41 lb/h.

In addition, HBA, COA, TLBO, cuckoo search algorithm (CSA), and PSO are also implemented, and the results are given in Table 3. From these results, it can be said that the HBA has a better ability to produce global optima. The improved voltage profiles for different scenarios are given in Fig. 1. The convergence characteristics of all these algorithms are given in Fig. 2.

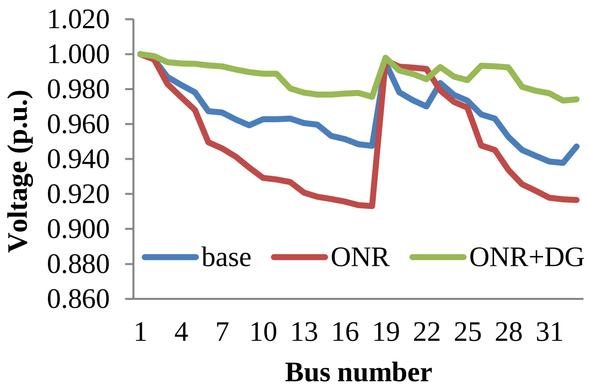

Figure. 1 Comparison of voltage profile for different scenarios

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Table 2. Solutions for simultaneous ONR and OADG problem without EV load

Method	**Open Switches**	**DGs in kW (bus #)**	**P_{loss} (kW)**	**AVD**	**GHG**
Base	33, 34, 35, 36, 37	-	202.6771	0.0515	8022.07
COA [2]	11, 27, 30, 33, 34	691 (18), 733.4 (29), 742.9 (8)	58.55	-	-
WCA [4]	11,28,31,33,34	960 (7), 750 (17), 1280 (25)	51.744	-	-
CTLHSO [8]	11, 28, 31, 33, 34	956.9 (7), 723 (17), 1279.6 (25)	50.72	-	-
SGA [9]	10, 28, 30, 33, 34	815.4 (18), 871.8 (25), 541.9 (26)	56.5589	-	-
CSGA [9]	7, 9, 14, 28, 30	469.7 (12), 1021.3 (25), 738. (33)	54.4788	-	-
ESCA [11]	7, 9, 14, 27, 30	567.23 (12), 712.5 (18), 1190 (25)	53.53	-	-
DS [16]	11, 28, 30, 33, 34	899.7 (7), 865.1 (18), 1295.6 (25)	51.3	-	-
ICA [17]	10, 14, 28, 31, 33	100 (32), 1000 (31), 653.3 (33)	73.19	-	-
BFO [18]	10, 14, 17, 20, 28	795 (13), 1069 (24), 1029 (30)	72.26	-	-
HAS [19]	7, 10, 14, 28, 32	525.8 (32), 558.6 (31), 584 (33)	73.05	-	-
HBA	**11, 28, 31, 33, 34**	**752.5 (17), 956.8 (7), 1280.34 (25)**	**50.718**	**0.00024**	**1588.41**

Table 3. Comparison of HBA with other algorithms without EV load

Method	**DG Locations**			**DG Sizes (kW)**			**P_{loss} (kW)**	**Q_{loss} (kVAr)**	**$V_{min,32}$**	**AVD (p.u)**	**GHG (lb/h)**
HBA	**17**	**7**	**25**	**752.54**	**956.84**	**1280.34**	**50.718**	**38.721**	**0.9734**	**0.00024**	**1588.41**
COA	25	7	17	1279.74	957.18	752.57	50.718	38.721	0.9734	0.00024	1588.41
TLBO	17	26	25	753.14	923.23	1286.43	51.657	39.749	0.9734	0.00024	1647.66
CSA	26	25	17	921.52	1287.15	753.06	51.657	39.750	0.9734	0.00024	1647.66
PSO	17	29	7	753.83	1148.87	988.68	51.777	39.696	0.9734	0.00024	1791.25

Table 4. Impact of EV load penetration on network performance

λ_{pen} (%)	**P_{load} (kW)**	**Q_{load} (kVAr)**	**P_{loss} (kW)**	**Q_{loss} (kVAr)**	**$V_{min,18}$**	**AVD (p.u)**	**GHG (lb/h)×10^3**
base	3715.00	2300.00	202.677	135.141	0.9131	0.00355	8022.07
10	4041.30	2367.18	231.876	154.541	0.9068	0.00407	8750.01
20	4744.98	2522.95	303.947	202.408	0.8929	0.00533	10338.48
30	5960.47	2808.28	458.155	304.757	0.8683	0.00798	13143.17
40	7927.91	3289.95	793.655	527.219	0.8270	0.01364	17858.80
50	11018.33	4062.53	1571.676	1042.594	0.7576	0.02658	25780.05

Table 5. Solutions for simultaneous ONR and OADG problem with EV load

λ_{pen} (%)	**DG Locations**			**DG Sizes (kW)**			**P_{loss} (kW)**	**Q_{loss} (kVAr)**	**$V_{min,32}$**	**AVD (p.u)**	**GHG (lb/h) ×10^3**
base	17	7	25	752.54	956.84	1280.34	50.718	38.721	0.9734	0.00024	1588.41
10	29	7	33	1252.67	1082.74	762.50	56.36	43.463	0.9732	0.00027	2064.42
20	8	25	33	537.79	1622.51	824.88	63.93	48.082	0.9717	0.00036	2998.96
30	25	26	33	1631.97	1183.51	879.66	66.31	51.748	0.9703	0.00033	2237.64
40	25	7	33	1737.76	1316.23	938.93	70.62	54.750	0.9687	0.00036	2325.96
50	7	25	16	1395.51	1861.31	1152.23	77.08	60.299	0.9617	0.00038	2175.01

5.3 Solution for simultaneous ONR and OADG problems with EV load penetration

In this case, step-wise EV load penetration is considered and, correspondingly, the ONR and OADG problems are solved simultaneously using HBA only. In this study, the operating power factor of the charging converter for EV loads is taken as 0.98. In order to understand the negative impact of EV load penetration on network performance, the

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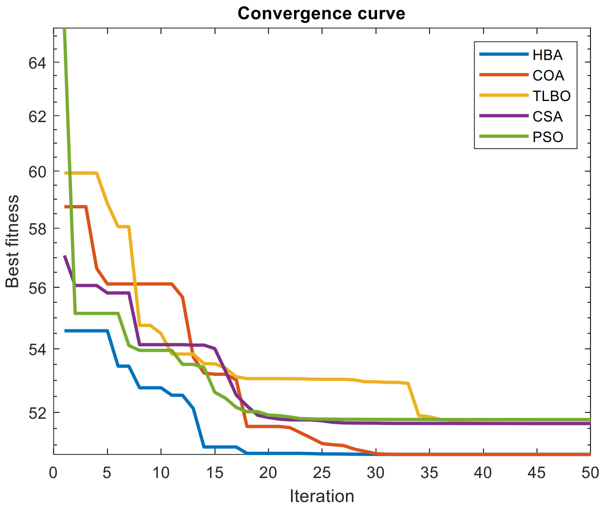

Figure. 2 Convergence characteristics of different algorithms

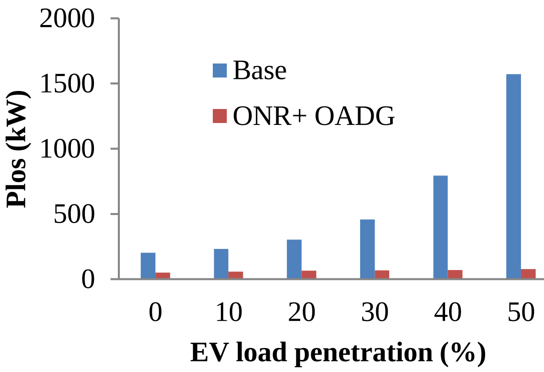

Figure. 3 Comparison of Ploss before and after ONR and DG allocation

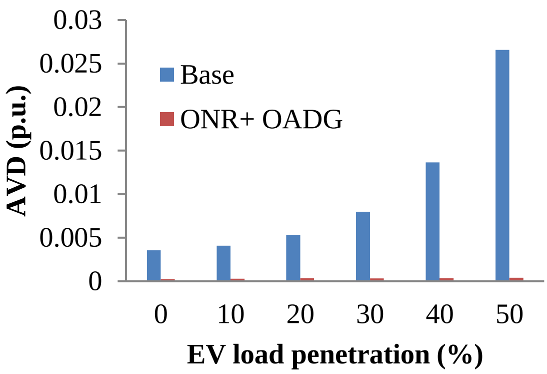

Figure. 4 Comparison of AVD before and after ONR and DG allocation

load flow is performed first, and the results are given in Table 4. It can be observed from the results that the loading levels are increased, losses are increased, the voltage profile is decreased, and GHG emissions are also increased significantly as EV load penetration increases.

In order to mitigate this negative impact, the ONR and OADG problems are solved, and the results are given in Table 5. From the results given

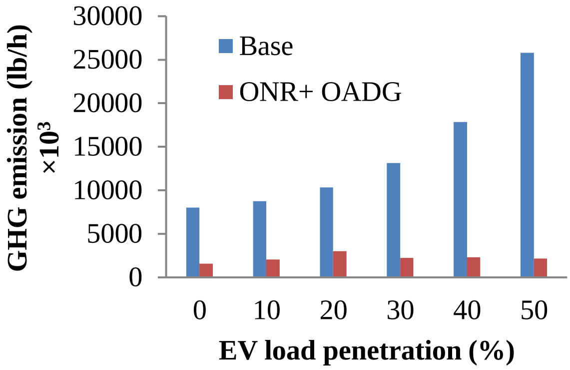

Figure. 5 Comparison of GHG emission before and after ONR and DG allocation

in Table 4 and 5, a comparison for base case test system performance and after DG allocation with network reconfiguration are given in Fig. 3 to 5, for real power losses, average voltage deviation and GHG emission, respectively. From these, it can be seen that the real and reactive power losses are decreased, the voltage profile is increased and GHG emissions are reduced significantly.

6. Conclusion

The rise in global temperature and greenhouse gas (GHG) emissions have become a motive four to adapt to renewable energy and electric vehicles in the energy and transportation sectors, respectively. Despite the environmental benefits, the intermittency and stochastic nature of these technologies have created various challenges in the operation and control of active distribution networks. In this paper, a novel heuristic approach is proposed for mitigating the negative impact on ADNs' performance by using optimal network reconfiguration and optimal allocation of distributed generation. A multi-objective function using real power losses, voltage deviation index, and GHG emissions is proposed and solved using a recent meta-heuristic honey badger algorithm. Simulation results were performed on the IEEE 33-bus radial distribution system for different EV load penetrations. The computational efficiency of HBA is compared with various literature works and also with COA, TLBO, CSA, and PSO. The results have shown the superiority of HBA over other algorithms, and the optimal reconfiguration and optimal DG allocation resulted in reduced losses, improved voltage profile, and reduced GHG emissions significantly.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, methodology, software and original draft preparation are done by Srinivasarao Thumati; supervision, review, and formal analysis are done by Vadivel V and Venu Gopala Rao M.

References

[1] A. O. Salau, Y. W. Gebru, and D. Bitew, "Optimal network reconfiguration for power loss minimization and voltage profile enhancement in distribution systems", *Heliyon*, Vol. 6, No. 6, e04233, 2020.

[2] I. B. Hamida, S. B. Salah, F. Msahli, and M. F. Mimouni, "Optimal network reconfiguration and renewable DG integration considering time sequence variation in load and DGs", *Renewable Energy*, Vol. 121, pp. 66-80, 2018.

[3] T. T. Nguyen, T. T. Nguyen, N. A. Nguyen, and T. L. Duong, "A novel method based on coyote algorithm for simultaneous network reconfiguration and distribution generation placement", *Ain Shams Engineering Journal*, Vol. 12, No. 1, pp. 665-76, 2021.

[4] M. A. Muhammad, H. Mokhlis, K. Naidu, A. Amin, J. F. Franco, and M. Othman, "Distribution network planning enhancement via network reconfiguration and DG integration using dataset approach and water cycle algorithm", *Journal of Modern Power Systems and Clean Energy*, Vol. 8, No. 1, pp. 86-93, 2020.

[5] A. Dogan and M. Alci, "Simultaneous optimization of network reconfiguration and DG installation using heuristic algorithms", *Elektronika ir Elektrotechnika*, Vol. 25, No. 1, pp. 8-13, 2019.

[6] M. M. Sayed, M. Y. Mahdy, S. H. A. Aleem, H. K. Youssef, and T. A. Boghdady, "Simultaneous Distribution Network Reconfiguration and Optimal Allocation of Renewable-Based Distributed Generators and Shunt Capacitors under Uncertain Conditions", *Energies*, Vol. 15, No. 6, 2299, 2022.

[7] I. A. Quadri, S. Bhowmick, and D. Joshi, "Multi-objective approach to maximise loadability of distribution networks by simultaneous reconfiguration and allocation of distributed energy resources", *IET Generation, Transmission & Distribution*, Vol. 12, No. 21, pp. 5700-5712, 2018.

[8] I. A. Quadri and S. Bhowmick, "A hybrid technique for simultaneous network reconfiguration and optimal placement of distributed generation resources", *Soft Computing*, Vol. 24, No. 15, pp. 11315-11336, 2020.

[9] T. H. Huy, T. V. Tran, D. N. Vo, and H. T. Nguyen, "An improved metaheuristic method for simultaneous network reconfiguration and distributed generation allocation", *Alexandria Engineering Journal*, Vol. 61, No. 10, pp. 8069-8088, 2022.

[10] M. N. Muhtazaruddin, J. J. Jamian, G. Fujita, M. A. Baharudin, M. W. Wazir, and H. Mokhlis, "Distribution network loss minimization via simultaneous distributed generation coordination with network reconfiguration", *Arabian Journal for Science and Engineering*, Vol. 39, pp. 4923-33, 2014.

[11] U. Raut and S. Mishra, "Enhanced sine–cosine algorithm for optimal planning of distribution network by incorporating network reconfiguration and distributed generation", *Arabian Journal for Science and Engineering*, Vol. 46, pp. 1029-1051, 2021.

[12] M. A. Abdelkader, Z. H. Osman, and M. A. Elshahed, "New analytical approach for simultaneous feeder reconfiguration and DG hosting allocation in radial distribution networks", *Ain Shams Engineering Journal*, Vol. 12, No. 2, pp. 1823-1837, 2021.

[13] N. Kanwar, N. Gupta, K. R. Niazi, A. Swarnkar, and R. C. Bansal, "Simultaneous allocation of distributed energy resource using improved particle swarm optimization", *Applied Energy*, Vol. 185, No. 2, pp. 1684-1693, 2017.

[14] S. Z. Jalil, M. N. Muhtazaruddin, N. A. Bani, S. A. Aris, H. M. Kaidi, A. Y. Fatah, J. J. Jamian, F. M. Sukki, and S. H. A. Bakar, "Distribution power loss minimization via distributed generation, capacitor and network reconfiguration", *Indonesian Journal of Electrical Engineering and Computer Science*, Vol. 5, No. 3, pp. 488-495, 2017

[15] K. Muthukumar and S. Jayalalitha, "Integrated approach of network reconfiguration with distributed generation and shunt capacitors placement for power loss minimization in radial distribution networks", *Applied Soft Computing*, Vol. 52, pp. 262-284, 2017.

[16] K. Jasthi and D. Das, "Simultaneous distribution system reconfiguration and DG sizing algorithm without load flow solution", *IET Generation, Transmission & Distribution*, Vol. 12, No. 6, pp. 1303-1313, 2017.

[17] M. Mohammadi, A. M. Rozbahani, and S. Bahmanyar, "Power loss reduction of distribution systems using BFO based optimal reconfiguration along with DG and shunt

capacitor placement simultaneously in fuzzy framework", *Journal of Central South University*, Vol. 24, No. 1, pp. 90-103, 2017.

[18] S. N. Ravadanegh, M. R. Oskuee, and M. Karimi, "Multi-objective planning model for simultaneous reconfiguration of power distribution network and allocation of renewable energy resources and capacitors with considering uncertainties", *Journal of Central South University*, Vol. 24, No. 8, pp. 1837-1849, 2017.

[19] R. S. Rao, K. Ravindra, K. Satish, and S. V. Narasimham, "Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation", *IEEE Transactions on Power Systems*, Vol. 28, No. 1, pp. 317-25, 2013.

[20] O. Badran, S. Mekhilef, H. Mokhlis, and W. Dahalan, "Optimal reconfiguration of distribution system connected with distributed generations: A review of different methodologies", *Renewable and Sustainable Energy Reviews*, Vol. 73, pp. 854-867, 2017.

[21] F. A. Hashim, E. H. Houssein, K. Hussain, M. S. Mabrouk, and W. A. Atabany, "Honey Badger Algorithm: New metaheuristic algorithm for solving optimization problems", *Mathematics and Computers in Simulation*, Vol. 192, pp. 84-110, 2022.

[22] T. K. Pandraju and V. Janamala, "Dynamic optimal network reconfiguration under photovoltaic generation and electric vehicle fleet load variability using self-adaptive butterfly optimization algorithm", *International Journal of Emerging Electric Power Systems*, Vol. 22, No. 4, pp. 423-437, 2021.

[23] S. Mishra, D. Das, and S. Paul, "A comprehensive review on power distribution network reconfiguration", *Energy Systems*, Vol. 8, No. 2, pp. 227-284, 2017.

[24] M. Mahdavi, H. H. Alhelou, N. D. Hatziargyriou, and A. A. Hinai, "An efficient mathematical model for distribution system reconfiguration using AMP", *IEEE Access*, Vol. 9, pp. 79961-79993, 2021.