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# Multi-objective optimal reconfiguration of distribution networks using a novel meta-heuristic algorithm

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**ABSTRACT**

Reconfiguration strategies are used to reduce power losses and increase the reliability of the distribution systems. Since the optimal reconfiguration problem is a multi-objective optimization problem with non-convex functions and constraints, meta-heuristic algorithms are the most suitable choice for the problem-solving approach. One of the new meta-heuristic algorithms that exhibits excellent performance in solving multi-objective problems is the wild mice colony (WMC) algorithm, which is implemented based on aggressive and mating strategies of wild mice. In this paper, the distribution network reconfiguration problem is solved to reduce power losses, improve reliability, and increase the voltage profile of network buses using the WMC algorithm. In addition, the obtained results are compared with conventional multi-objective algorithms. The optimal reconfiguration problem is applied to the IEEE 33-bus and 69-bus test systems. The comparative study confirms the superior performance of the proposed algorithm in terms of convergence speed, execution time, and the final solution.



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## 1. INTRODUCTION

Owing to the massive increase in the demand for electric energy, it is necessary to strengthen and develop power networks at production, transmission, and distribution levels [1]. Since the distribution network is the last sector of the electricity supply chain connecting the loads to the transmission lines, it operates under low-voltage voltage conditions and thus suffers from considerable power losses. On the other hand, due to the large extent of these networks and the extensive number of equipment, maintaining their reliability is very critical [2], [3]. Distribution network reconfiguration (DNR) is an operation in which by changing the state of the tie and sectionalizing switches, the topology of the network is changed so that certain constraints are met and the objective function (s) is (are) optimized [4], [5]. This problem is a multi-objective complex and non-convex problem due to including numerous objectives [6].

Numerous techniques have been proposed in the literature to solve the multi-objective DNR problem, including mathematical, heuristic, and meta-heuristic methods. The contribution of meta-heuristic methods in solving the DNR problem is more than the other two methods [7], [8]. Several optimization methods have been recently introduced. These include heap-based optimization [9], the SHADE optimization algorithm combined with the switch opening and exchange (SOE) method [10], the combined simulated annealing (SA) and modified particle mass optimization (MPSO) algorithms [11], mixed-integer linear programming (MILP) [12], the combined conventional particle swarm optimization and binary particle swarm optimization (BPSO) [13], the enhanced artificial bee colony optimization (EABCO) method [14], the chaotic stochastic fractal search algorithm (CSFSA) [15], hybrid improved particle swarm optimization-artificial bee colony optimization algorithm [16], the grasshopper optimization algorithm [17], and the modified sequential switch opening and exchange (MSSOE) [18].

A general comparison has been made in [19] between mathematical models and meta-heuristic methods to solve the DNR problem, which reveals that meta-heuristic algorithms are superior from the quality of solution and computational burden points of view. In study [20], the COOT and Aquila optimization algorithms have been used for optimal planning of thermal energy storage. The combination of two conventional meta-heuristic algorithms called the gray wolf whale optimization algorithm (GWWOA) has been proposed in [21]. The ant lion optimization (ALO) algorithm is also a newly introduced algorithm that has been utilized to solve the dynamic economic emission dispatch problem [22]. A modified version of the conventional bee colony optimization algorithm has been provided in [23], which aims for adaptive power scheduling in a power system. Amar *et al.* [24] have proposed the cat swarm meta-heuristic optimization method for the optimal design of a power system consisting of wind units, which pursues three goals, i.e., optimization of cost, capacity, and reliability.

Most meta-heuristic algorithms in multi-objective form, e.g., BPSO, moth-flame optimization (MFO), and ABCO, suffer from low speed due to employing one or two tools to search for the objective. Thus, the performance of such algorithms in solving dynamic optimization problems is weakened. Furthermore, developing a meta-heuristic optimization algorithm to address multi-objective optimization problems without adding additional search tools or combining them with other optimization algorithms is a meaningful challenge. Most of the studies conducted in this field have shortcomings from the point of view of simultaneous optimization of objective functions. To cope with the aforementioned limitations, this paper proposes a new meta-heuristic algorithm called the wild mice colony (WMC) algorithm to solve the DNR problem. This algorithm is based on the natural behavior of a colony of wild mice in recruitment, new colony formation, and mating. Since there are multiple searching tools for the optimal solution, the WMC algorithm has outstanding performance in solving complex optimization problems; hence, it is suitable for solving the DNR problem for large-scale systems. In terms of convergence speed and execution time, a comparison between the proposed WMC algorithm and other conventional multi-objective algorithms is accomplished in this paper. In addition, the proposed WMC algorithm is tested on two standard IEEE 33-bus and 69-bus systems, which are used in most studies.

The rest of the paper is organized as follows. The formulation of the proposed optimization problem, along with the objectives and constraints, are presented in section 2. The third section explains the problem-solving process and the proposed WMC algorithm. The numerical results of solving the optimization problem using the proposed WMC algorithm are presented in section 4. Finally, the fifth section concludes the article.

## 2. OPTIMIZATION PROBLEM FORMULATION

In this paper, the following objective functions are included in the objective function: active power losses, voltage profile, and reliability. Each objective is described in detail and formulated in the subsections. Eventually, the final combined objective function is obtained by summing the individual objectives.

### 2.1. Power loss minimization

The first objective function is to minimize the active power losses of the distribution network feeders. According to Figure 1, this objective is defined as (1) [9].

$$min \;\; P_{loss} = \sum_{i=1}^{nb} r_i \frac{P_i^2+Q_i^2}{V_i^2}) \tag{1}$$

where *nb* is the number of nods, $r_i$ is resistance of the branch *i*. $P_i$, $Q_i$, and $V_i$ represent the active power, reactive power, and the voltage of the node *I*, respectively.

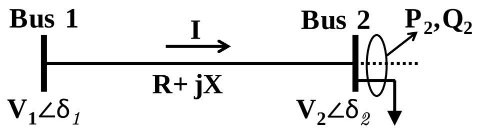



Figure 1. Simple-line two-bus distribution system

### 2.2. Reliability improvement

An analytical method based on cut-set analysis is used in this paper to avoid complicated simulation efforts. The minimal cut-set is a set of system elements whose failure causes the system to fail. On the contrary, if any of these elements work appropriately, the system operation will not be affected. The probability of a cut-set is calculated using (2).

$$P(C) = \prod_i Q_i) \tag{2}$$

where $Q_i$ is the unreliability corresponding to the $i^{th}$ cut-set. Next, the unreliability of the system will be calculated by serializing the cut-sets from (3):

$$Q_i = P(\cup_i C_i), i = 1,2, \ldots, N) \tag{3}$$

For reliability assessment, the radiality of the studied distribution system is checked before performing any calculations. So, we can claim that there is only one path to feed each load when calculating the reliability indices. Thus, reliability can be obtained as $R_i = 1 - Q_i$. One of the most common reliability indices is the energy not served (ENS). After performing the reliability calculations using the minimal cut-set method, it is easy to calculate the ENS for each load. Their summation gives the total ENS for the whole system, as defined in (4).

$$min \;\; ENS = \sum_{i=1}^{nb} L_i^{avr} U_i) \tag{4}$$

where $L_i^{avr}$ is the average load connected to the bus $i$, $U_i$ is the annual unavailability which is $U_i = 8760 \times Q_i$, and $nb$ is the number of system buses. Also, the customer average interruption duration index (CAIDI) is defined as (5):

$$min \;\; CAIDI = \frac{SAIDI}{SAIFI}) \tag{5}$$

where the system average interruption duration index (SAIDI), and the system average interruption frequency index (SAIFI) are obtained via:

$$SAIDI = \frac{\sum_i ACIT_i \times C_i}{\sum_i C_i} \tag{6}$$

$$SAIFI = \frac{\sum_i ACIF_i \times C_i}{\sum_i C_i} \tag{7}$$

$$ACIT_i = \sum_k \left(8760 \times P_{rk} \times frac_{i,k}\right) \tag{8}$$

$$ACIF_i = \sum_k \left(P_{rk} \times \; frac_{i,k}\right) \tag{9}$$

In (6) to (9), $C_i$ is the number of loads connected to the $i^{th}$ bus, $P_{rk}$ and $frac_{i,k}$ are the probability of losing the $k^{th}$ load, and the amount of lost load connected to the $i^{th}$ bus, respectively. Also, $ACIT_i$ and $ACIF_i$ show the average duration of interruption ($h/a$), and the average number of interruptions per customer ($1/a$) per year, respectively.

### 2.3. Voltage profile enhancement

Taking into account the average voltage difference of all buses compared with the reference bus, the third objective function, i.e., the voltage profile enhancement is defined as (10).

$$min \;\; V_D = \sum_{i=1}^{nb} \frac{|V_b - V_i|}{V_b}) \tag{10}$$

where $V_D$ is the voltage deviation index. $V_b$ and $V_i$ are the nominal voltage and the real voltage of $i^{th}$ bus, respectively. $nb$ also indicates the number of buses.

### 2.4. The proposed objective function

Eventually, the proposed objective function can be defined as (11).

$$min \;\; f = c_1 P_{loss} + c_2 ENS + c_3 CAIDI + c_4 V_D) \tag{11}$$

where $c_j$ ($j$=1,2,3,4) represent the weighting coefficients which are selected equal to 1 in this study.

### 2.5. Constraints

The following constraints should be considered in the problem-solving procedure. The permitted voltage of buses constraint:

$$V_{min} < V_i < V_{max}) \tag{12}$$

where $V_{min}$ and $V_{max}$ are the minimum and maximum voltage allowed for the $i^{th}$ branch. Feeder current constraint:

$$|I_k| \leq I_{kmax}) \tag{13}$$

#### 2.5.1. Distribution network radiality constraint

The distribution network must always maintain its radiality in all the structures obtained by the reconfiguration process. To comply with this requirement, in the case where there is a feeding substation, the number of branches must be equal to the number of buses minus 1, as (14).

$$rank\ (\mathrm{A}) = nb - 1) \tag{14}$$

where $A$ denotes the node-to-branch incidence matrix, and *rank* $(A)$ represents the number of linearly independent rows or columns of $A$.

## 3. METHOD

In this section, the solving procedure for the proposed multi-objective optimization problem is presented. Before executing the optimization algorithm, an AC load flow is conducted to obtain the initial values of the technical parameters of the system. It is noteworthy that the backward/forward load flow strategy is employed in this study.

### 3.1. Optimization algorithm

In this paper, a novel meta-heuristic algorithm is proposed, which is inspired by the behaviorism of wild mice colonies (WMCs). The foundation of this algorithm is the collaborative effort of the wild mice colonies to extend the colony. Each colony has a particular behavioral mechanism that leads the algorithm to find optimal solutions. During the optimality searching procedure, the WMC algorithm executes different phases that enhance solution-reaching tools. The WMC algorithm phases are described in the following.

#### 3.1.1. Generating the initial population

Firstly, the initial population (IP) is created within the problem space. It is worth noting that the IP is equal to the product of the number of colonies by the number of members within the colony (e.g., $IP = number\ of\ colonies \times 12$). Among this population, the number of male and female mice is determined based on the predefined parameter (e.g., $male\ mice\ number = \frac{1}{3} \times IP$, $female\ mice\ number = \frac{2}{3} \times IP$). Next, the highest-priority male mice create their colony.

#### 3.1.2. Determining the best male mice for creating colonies

In the experiment conducted on mice, a rule named mice norm (MN) specifies their class preference. Indeed, mice with large NM values have a higher priority and can successfully create a new colony or mate. The initial population is sorted according to the NM criterion, and the high-sorted male mice are chosen to construct their colony or territory. The TYPE of these mice is changed to colony head (CH).

#### 3.1.3. Determining the male and female members of the colonies

For each colony within the IP, members are recruited randomly. It is assumed in this study that each CH randomly selects 3 male and 8 female mice as the colony members. According to the results obtained from laboratory tests, it has been revealed that the age of female mice is influential in their social interactions. In other words, the younger female mice have a higher chance to mate. Furthermore, the NM value depends on the colony density. The higher the colony density, the lower the NM value in that colony. Two independent procedures are executed for normal members and CH to adjust the position of mice in each repetition of the algorithm. The movement of each CH is according to the best of the other CHs. In Figure 2, the movement range of CHs belonging to 4 colonies is specified. As can be seen, the CHs move toward the other colonies to identify female mice prone to mating.

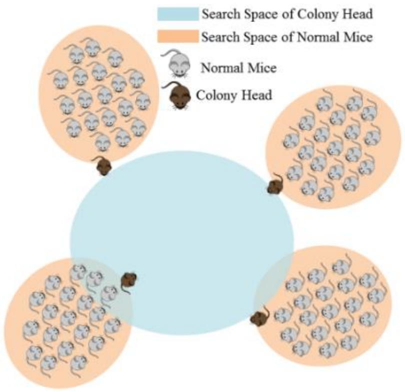
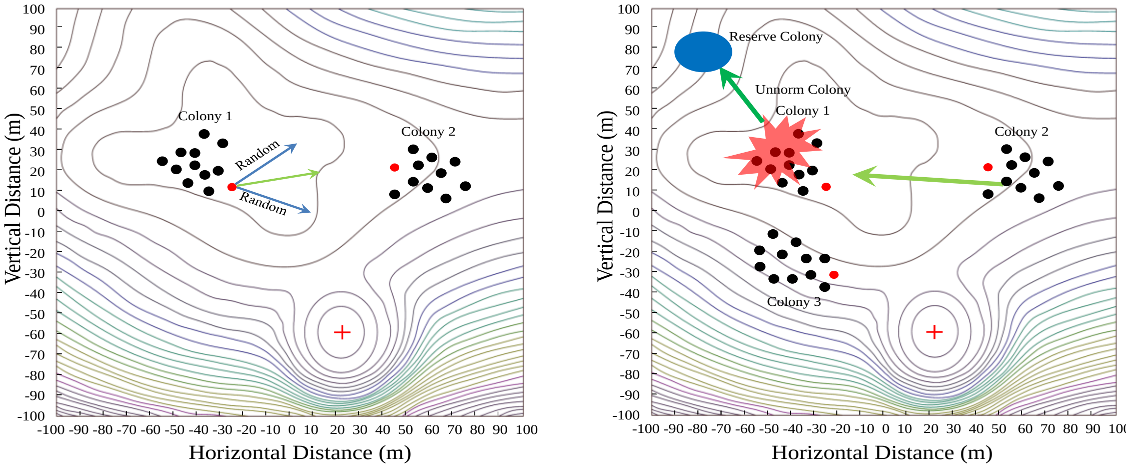



Figure 2. The movement space of CHs

#### 3.1.4. Male and female mice mating

Figure 3(a) shows the movement path of the two colonies in a (200×200)$m^2$ hypothetical area. In order to execute the mating process, the best CH among all colonies (having the higher priority) is selected and mates with female mice belonging to another colony whose accept parameter (AP) is 1. The AP of female mice will be equal to 1 if they are in the mating phase, and their age is less than a threshold. Mating takes place three times a year. Therefore, the mating factor is obtained by dividing the number of iterations by 3. The CH mice randomly mate with female mice under three conditions and generate 5 to 15 new mice. The mating conditions are as follows: i) the selected member among the target colony is female, ii) the accept parameter of the selected member equals 1, and iii) the age of the selected member is less than the threshold.

The gender of the new generation of mice is randomly determined. The newborn mice find their position using the nonlinear quadratic crossover operator. Then, the generated offspring fight with the young population of the same colony, and the weaker members are expelled to create a “reserve colony”, as shown in Figure 3(b). The remaining mice attack the next colony to recruit new members, including 4 male and 8 female mice. If the next colony does not have the desired number of female or male mice, this shortage of members is absorbed from the reserve colony. The cost function corresponding to the newly created colony is calculated in each iteration, and the procedure is repeated until the stopping criterion is met. In the next step, the global best colony and best mice belonging to the best colony are determined as the optimization solution. Algorithm 1 shows the pseudo-code of the WMC algorithm.




(a) (b)

Figure 3. The hypothetical area for analyzing the behavior of the Mice colonies, (a) the CH movement to find the female mice and (b) the reserve colony creation process

### 3.2. Applying the proposed algorithm to the DNR problem

There are two types of switches in a distribution network, i.e., normally closed (NC) and normally open (NO). Suppose that all NOs are closed. In this case, several loops are formed in the system, and their number is equal to the number of NOs. The switches set that form a loop are called loop vector (LV). In the proposed method, one colony is assigned for each LV, and one of the switches in each LV must always be open. This ensures the radiality of the distribution network structure. The flowchart of the proposed Algorithm 1 implementation for solving the DNR problem is depicted in Figure 4.

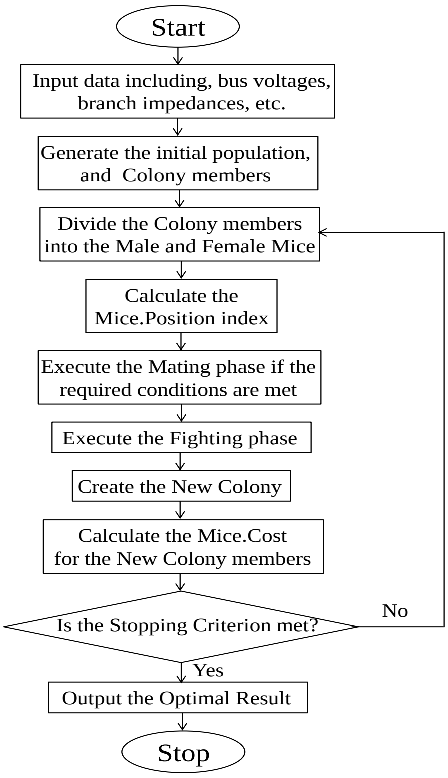



Figure 4. Flowchart of the proposed WMC algorithm for solving the DNR problem

Algorithm 1. Pseudocode of WMC optimization algorithm

1. Start
2. Determine the maximum iteration ($MaxItr$)
3. Generate the initial population ($N$)
4. Generate the colonies with $M$ members
5. Divide the colony into $m$ Male and $f$ Female Mice
   Colony(j).index = $\text{rand}[(mice.sec = m):3] \times rand[(mice.sec = f):8]$
6. Determine the age threshold ($AgeThre$)
7. Determine the Colony Norm ($CN$)
   For $j$=1,2,…,$N$
   If Std $\sum_{j=1}^{n}$ (mice(j).Position ) < Treshold
   mice(j).Norm = mice(j).Norm - 1
8. Define the Position of Normal Mice
   $mice(j).Position_{Normal\ Mice} =$
   $mice(j).Position + rand(j) \times (mean(\sum_{k=1}^{M} mice(k).Position - mice(j).Position)$
9. Determine the Position of Colony Head ($CH$)
   $mice(j).Position_{Colony\ Head} =$ mice(j).Position+rand(j)×(best(CH)−mice(j).Position)
10. Execute the Mating Process:
   Determine the Mating Accept parameter for Female Mice
   $MatingCount = \frac{Iteration}{2}$
   For $j$=1,2,…,$N$
   For $k$=1,2,…,$f$
   If $iteration$=$MaxItr$
   mice(j).accept=1;

```
        else If
        For i=1,2,…,m & k=1,2,…,f
        If mice(i).Norm = Max & mice(k).sec = f & mice(k).accept = 1 & mice(k).age ≥ AgeThr
        The Mating is executed.
           mice(i).couple = MatingCount = MatingCount+1, mice(k).accept = 0
11. Execute Fighting phase:
        For j=1,2,…,N
           For k=1,2,…, M
           mice(j).delete = 1/2 × (sort ∑_{k=1}^{M} (mice(j).cost)
12. Create new Colony in Reservation by Invader Mice:
    NewColony(j).Index =[(mice(j).sec = m):3] × rand[(mice(j).sec = f):8]
13. Determine the Best Mice belonging to the new Colony:
    ColonyGBest=min(mice(j).cost)
14. Determine the Global Best of Total Colony:
    GBest=min(ColonyGBest)
15. Stop
```

## 4. RESULTS AND DISCUSSION

In this section, to confirm the effectiveness of the proposed optimization WMC algorithm, the predefined DNR problem is solved for two distribution networks, i.e., IEEE 33-bus and 69-bus test systems, and the obtained results are analyzed. The simulations are carried out in MATLAB R2018b using a Core i7, 2.4 GHz processor, 8 GB RAM computer. The 33-bus and 69-bus distribution systems initial data are given in [9]. Also, Table 1 gives the parameters of the proposed WMC algorithm.

Table 1. Parameters of the proposed WMC algorithm

| Parameter | Value |
|---|---|
| Initial population | 108 |
| Number of colonies | 9 |
| Number of male mice per colony | 4 |
| Number of female mice per colony | 8 |
| Initial mice norm (MN) | 0.1 |
| Initial accept parameter (AP) | 0 |
| Maximum iteration | 200 |
| Mating age threshold (Age threshold) | 8 months |
| Maximum radius of colonies (Position threshold) | 10 m |

### 4.1. Case study 1: IEEE 33-bus test system 1

The IEEE 33-bus system, as shown in Figure 5, has a feeder substation and 32 buses. This network includes 5 open branches (tie switches or NO switches represented by red dash lines in Figure 5) and 32 closed branches. The nominal voltage level is 12.66 kV, and the network's total active and reactive power consumption under normal conditions are 3,715 kW and 2,300 kVAr, respectively.

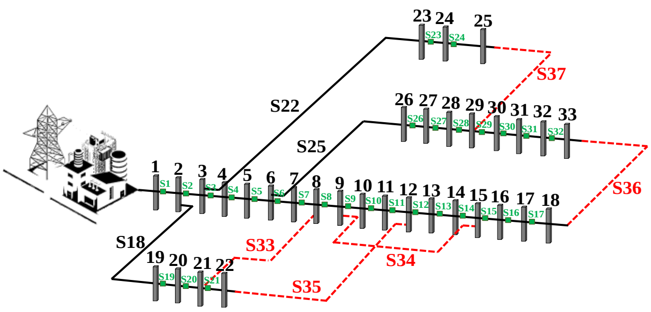



Figure 5. IEEE 33-bus test system

The optimization results are presented in two states, i.e., before the distribution network reconfiguration and after the distribution network reconfiguration. The results obtained by applying the proposed WMC algorithm for the 33-bus system are given in Table 2. According to Table 2, it is confirmed that after the reconfiguration, the total active power losses decreased from 202.67 to 108.7921 kW. The energy not served reaches 40.1981 kWh/y, which indicates a decrease of 22.03%. The CAIDI index also reduced from 5.5851 to 4.5403, and the SAIFI index decreased from 2.5966 to 1.9054. This reveals the impact of the reconfiguration in increasing the reliability indices. In addition, Figure 6 shows the voltage profile before and after reconfiguration for the 33-bus system. It can be seen that the reconfiguration has a satisfactory effect on the voltage profile so that the minimum voltage has increased from 0.9338 p.u to 0.9543 p.u.

Table 2. Numerical results for IEEE 33-bus system

| Parameter | Before reconfiguration | After reconfiguration |
|---|---|---|
| Total Active power losses (kW) | 202.67 | 108.7921 |
| Minimum voltage profile (p.u) | 0.9338 | 0.9543 |
| The opened switches | 33‹34‹35‹36‹37 | 7‹9‹14‹32‹37 |
| Energy not served (kWh/y) | 51.5579 | 40.1981 |
| SAIFI index | 5.5854 | 4.5403 |
| CAIDI index | 2.5966 | 1.9054 |

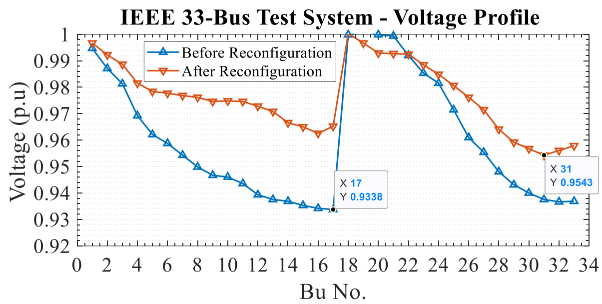



Figure 6. Voltage profile before and after reconfiguration for IEEE 33-bus test system

### 4.2. Case Study 2: IEEE 69-bus test system

The IEEE 69-bus network has one feeder substation and 68 buses, as depicted in Figure 7. The branches specified by red dash lines are normally open, and the other switches are normally closed. The nominal voltage level is 12.66 kV and the total active and reactive power consumption under normal conditions are 3802.19 kW and 2694.6 kVAr, respectively. Similarly, the numerical results are presented in Table 3. According to Table 3, it can be seen that after the reconfiguration, the total active power losses have decreased from 224.9804 kW to 94.6574 kW. Also, the ENS index has diminished from 462.3 kWh/y to 251.4 kWh/y, which means a 45.62% decrease in this index. The CAIDI index decreased from 4.6791 to 2.2593, and the SAIFI index reduced from 2.7654 to 1.2684. This indicates the effectiveness of the reconfiguration process in increasing the reliability indices. In addition, the voltage profile curves before and after reconfiguration are depicted in Figure 8 for the IEEE 69-bus test system. According to this figure, it can be seen that the reconfiguration decreases the voltage deviation index considerably so that the minimum voltage has increased from 0.9078 p.u to 0.9584 p.u.

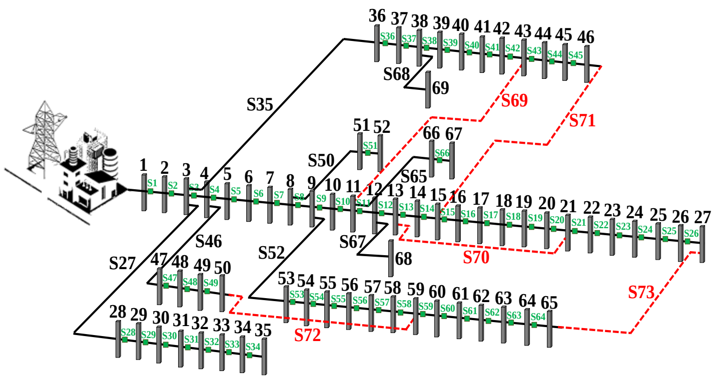



Figure 7. IEEE 69-bus test system

Table 3. Numerical results for the IEEE 69-bus system

| Parameter | Before reconfiguration | After reconfiguration |
|---|---|---|
| Total Active power losses (kW) | 224.9804 | 94.6574 |
| Minimum voltage profile (p.u) | 0.9078 | 0.9584 |
| The opened switches | 69،70،71،72،73 | 12،20،56،61،69 |
| Energy not served (kWh/y) | 462.3 | 251.4 |
| SAIFI index | 2.7654 | 1.2684 |
| CAIDI index | 4.6791 | 2.2593 |

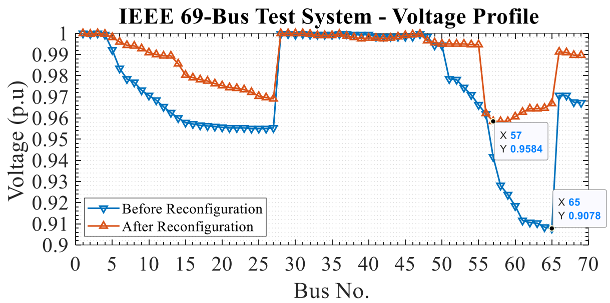



Figure 8. Voltage profile before and after reconfiguration for the IEEE 69-bus test system

### 4.3. Comparative study

Table 4 gives the results of the proposed algorithm WMC compared to other methods presented in the literature corresponding to the IEEE 33-bus and 69-bus test systems under the normal load conditions. Furthermore, Figure 9 illustrates the objectives, i.e., Figure 9(a) $P_{Loss}$, Figure 9(b) ENS, Figure 9(c) CAIDI, and Figure 9(d) $V_D$, obtained by applying enhanced genetic algorithm (EGA) [25], binary particle swarm optimization (BPSO) [26], teaching-learning-based optimization (TLBO) [27], and selective particle swarm optimization (SPSO) [28] optimization algorithms for the IEEE 33-bus test system. As can be seen in this figure, the algorithm proposed in this study has superior performance compared to other algorithms presented in the literature from the convergence characteristics and the final value of the objective function points of view. Since the proposed WMC algorithm works based on aggressive and mating behaviors of wild mice in the separated colonies, it can simultaneously calculate different cost functions for new colony members and distinguish the most optimal values. This capability is not seen in other multi-objective optimization algorithms, e.g., BPSO and EGA, where the multi-objective structure of the algorithm is different from the single-objective structure. In other words, the optimization algorithm calculates each objective in an independent step to optimize multiple objectives, and the optimal value is obtained by sorting the results in descending order. This will increase the execution time of conventional multi-objective algorithms, especially for complex optimization problems. In contrast, the proposed WMC algorithm does not depend on the number of objective functions, so its execution speed is higher. In addition, due to the classification of the initial solution space (initial population) in the proposed algorithm based on the age, gender, and position indices of mice, searching the whole possible solution space is more accessible, and the convergence speed of the algorithm will be increased.

In order to further investigate, the percentage of power loss reduction and the percentage of minimum voltage enhancement for IEEE 33-bus and 69-bus test systems by applying different optimization algorithms are compared in Figures 10 and 11, respectively. The active power loss reduction and the minimum voltage enhancement in percentage for the 33-bus system are depicted in Figures 10(a) and 10(b), respectively. The same representations are also provided for 69-bus system in Figures 11(a) and 11(b), respectively. By executing the proposed WMC algorithm, the power loss reduction percentage for IEEE 33-bus and 69-bus systems is 46.3206% and 57.9264%, respectively. Furthermore, the minimum voltage enhancement percentage by solving the optimization problem using the proposed WMC algorithm is 2.1953% and 5.5739% for IEEE 33-bus and 69-bus systems, respectively. These results confirm that the proposed WMC algorithm performs better than other optimization algorithms from the power loss minimization and voltage profile enhancement points of view for the 69-bus test system. However, in the case of the 33-bus system, despite the superiority of the proposed algorithm in power loss minimization, the WMC algorithm ranks second after the gravitational search algorithm (GSA) algorithm from the voltage profile enhancement viewpoint. This result verifies that the proposed WMC algorithm has outstanding performance in solving DNR problems for large-scale distribution systems despite its satisfactory performance for small-scale distribution systems.

Table 4. The comparative study results Associated with the IEEE 33-bus and 69-bus test systems

| Algorithm | Total active power loss (kW) | | Minimum voltage (p.u) | | Maximum iteration until convergence |
|---|---|---|---|---|---|
| | 33-bus system | 69-bus system | 33-bus system | 69-bus system | |
| HBO [9] | 138.01 | - | 0.94234 | - | ~ 7 |
| MILP [12] | 139.55 | 99.61 | 0.9378 | 0.9427 | - |
| MPSO [13] | 131.0 | 98.86 | 0.9394 | 0.95239 | ~ 20 |
| CSFSA [15] | 138.91 | - | 0.94235 | - | ~ 18 |
| MSSOE [18] | 139.55 | 99.69 | 0.9378 | 0.9428 | - |
| EGA [25] | 139.55 | 99.62 | - | - | ~ 90 |
| BPSO [26] | 138.928 | 98.595 | 0.9378 | 0.9495 | ~ 60 |
| TLBO [27] | 139.52 | 99.55 | 0.9378 | 0.9428 | ~ 75 |
| SPSO [28] | 138.92 | 98.59 | 0.9423 | 0.9494 | ~ 25 |
| WMC (This Work) | 108.7921 | 94.6574 | 0.9543 | 0.9584 | ~ 21 - 23 |

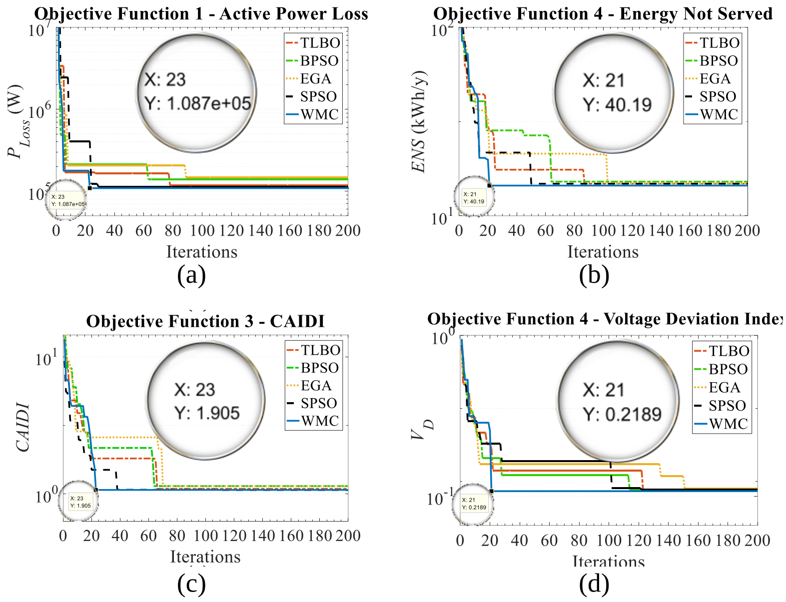



Figure 9. Convergence characteristics of the optimization algorithms for the normal load scenario–IEEE 33-bus test system, (a) active power loss, (b) energy not served (ENS), (c) CAIDI index, and (d) voltage deviation

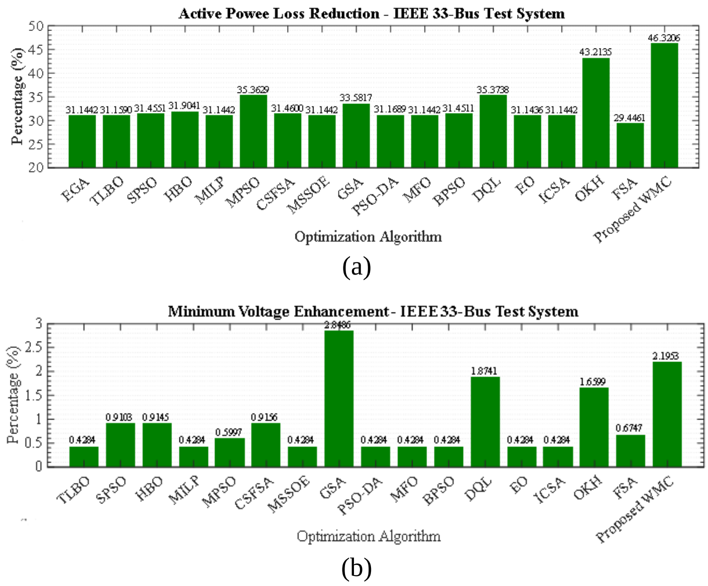
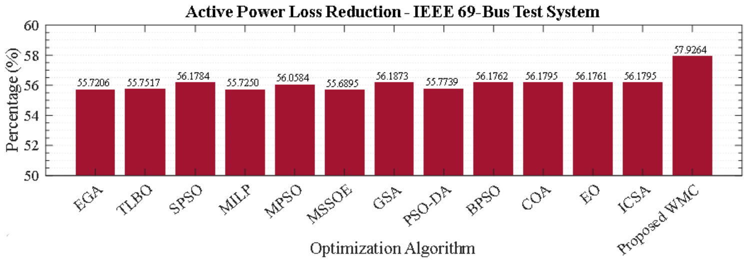
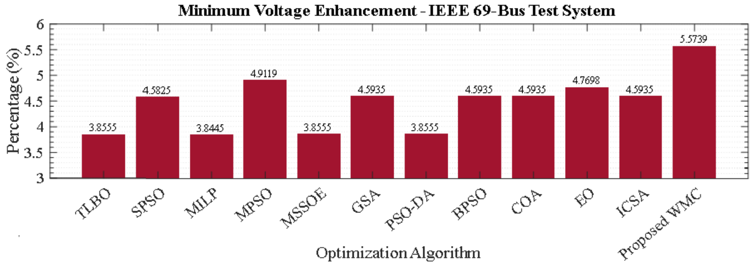



Figure 10. Comparative study results for the IEEE 33-bus test system (a) power loss reduction percentage and (b) minimum voltage enhancement percentage




(a)




(b)

Figure 11. Comparative study results for the IEEE 69-bus test system (a) power loss reduction percentage and (b) minimum voltage enhancement percentage

## 5. CONCLUSION

A new meta-heuristic algorithm named the WMC algorithm is proposed in this paper to solve the optimal distribution network reconfiguration DNR problem. A multi-objective optimization problem including minimizing active power loss, improving reliability indices, and enhancing voltage profile, is defined and solved using the proposed algorithm for two IEEE 33-bus and 69-bus test systems. In addition, four recently proposed optimization algorithms, i.e., EGA, BPSO, TLBO, and SPSO, are also applied, and the results are compared with the proposed WMC algorithm to evaluate the performance of the proposed algorithm in solving the DNR problem. The numerical results confirm the superiority of the proposed WMC algorithm compared to other algorithms in terms of convergence speed and the converged objective function value. Furthermore, a comparative study is accomplished with literature. The comparison of the power loss reduction percentage demonstrates that the proposed WMC algorithm results in the highest loss reduction among the optimization algorithms utilized in the literature to solve the DNR problem with 46.3206% and 57.9264% loss reduction for 33-bus and 69-bus systems, respectively. In addition, the proposed algorithm performs satisfactorily in increasing the minimum voltage so that it ranks second for the first case study while exhibiting the best performance for the second case study. This result confirms that the proposed WMC algorithm is a great candidate for solving the DNR problem for large-scale distribution networks. In addition, the proposed algorithm is not limited to the number of objectives, which is a noteworthy advantage. According to the acquired results, the proposed WMC algorithm can solve the DNR problem, including four objective functions, with higher convergence speed and accuracy compared with the EGA, BPSO, TLBO, and SPSO algorithms. By implementing the proposed method of determining the optimal configuration of the system in this paper, it is possible to make early and timely decisions in the event of faults in the power systems, which ultimately prevents extensive blackouts and damage to other parts of the system. On the other hand, the performance of protection relays in the system depends on the timely sending of control commands from the distribution system operator (DSO). Most of the strategies presented in the studies to determine the optimal configuration of the system challenge the system operator due to the long execution and presentation of results. In the next study, the optimal reconfiguration of the distribution network with high penetration of distributed generation units and plug-in electric vehicles will be investigated. In such a system, due to the presence of sensitive loads, fault propagation throughout the system can cause significant economic losses to the system; hence, it is critical to determine the optimal system configuration as soon as possible.

## REFERENCES

[1] W. Strielkowski, L. Civín, E. Tarkhanova, M. Tvaronavičienė, and Y. Petrenko, "Renewable energy in the sustainable development of electrical power sector: a review," *Energies*, vol. 14, no. 24, Dec. 2021, doi: 10.3390/en14248240.
[2] M. A. A. Al-Jaafreh and G. Mokryani, "Planning and operation of LV distribution networks: a comprehensive review," *IET*

*Energy Systems Integration*, vol. 1, no. 3, pp. 133–146, Jul. 2019, doi: 10.1049/iet-esi.2019.0013.
[3] A. Landeros, S. Koziel, and M. F. Abdel-Fattah, "Distribution network reconfiguration using feasibility-preserving evolutionary optimization," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 3, pp. 589–598, Dec. 2019, doi: 10.1007/s40565-018-0480-7.
[4] S. Kazmi, A. Janjua, and D. Shin, "Enhanced voltage stability assessment index based planning approach for mesh distribution systems," *Energies*, vol. 12, no. 2, Jan. 2019, doi: 10.3390/en12020275.
[5] B. K. Talukdar, B. C. Deka, A. K. Goswami, and D. Saha, "Reconfiguration of radial distribution network implementing TLBO algorithm for loss minimization and reliability improvement," in *Learning and Analytics in Intelligent Systems*, vol. 12, Springer International Publishing, 2020, pp. 157–164.
[6] H. Lotfi, A. Azizivahed, A. A. Shojaei, S. Seyedi, and M. F. Bin Othman, "Multi-objective distribution feeder reconfiguration along with optimal sizing of capacitors and distributed generators regarding network voltage security," *Electric Power Components and Systems*, vol. 49, no. 6–7, pp. 652–668, Apr. 2022, doi: 10.1080/15325008.2021.2011486.
[7] M. Mahdavi, H. H. Alhelou, N. D. Hatziargyriou, and F. Jurado, "Reconfiguration of electric power distribution systems: comprehensive review and classification," *IEEE Access*, vol. 9, pp. 118502–118527, 2021, doi: 10.1109/ACCESS.2021.3107475.
[8] 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, Jun. 2020, doi: 10.1016/j.heliyon.2020.e04233.
[9] D. Otuo-Acheampong, G. I. Rashed, A. M. Akwasi, and H. Haider, "Application of optimal network reconfiguration for loss minimization and voltage profile enhancement of distribution system using heap-based optimizer," *International Transactions on Electrical Energy Systems*, vol. 2023, pp. 1–17, Apr. 2023, doi: 10.1155/2023/9930954.
[10] M. M. Sayed, M. Y. Mahdy, S. H. E. Abdel Aleem, H. K. M. 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, Mar. 2022, doi: 10.3390/en15062299.
[11] R. Sellami *et al.*, "Optimal reconfiguration of distribution network considering stochastic wind energy and load variation using hybrid SAMPSO optimization method," *Sustainability*, vol. 14, no. 18, Sep. 2022, doi: 10.3390/su141811208.
[12] L. A. Gallego Pareja, J. M. López-Lezama, and O. Gómez Carmona, "Optimal feeder reconfiguration and placement of voltage regulators in electrical distribution networks using a linear mathematical model," *Sustainability*, vol. 15, no. 1, Jan. 2023, doi: 10.3390/su15010854.
[13] S. Essallah and A. Khedher, "Optimization of distribution system operation by network reconfiguration and DG integration using MPSO algorithm," *Renewable Energy Focus* , vol. 34, pp. 37–46, Sep. 2020, doi: 10.1016/j.ref.2020.04.002.
[14] H. Lotfi, "Multi-objective network reconfiguration and allocation of capacitor units in radial distribution system using an enhanced artificial bee colony optimization," *Electric Power Components and Systems*, vol. 49, no. 13–14, pp. 1130–1142, Aug. 2022, doi: 10.1080/15325008.2022.2049661.
[15] T. Tran The, D. Vo Ngoc, and N. Tran Anh, "Distribution network reconfiguration for power loss reduction and voltage profile improvement using chaotic stochastic fractal search algorithm," *Complexity*, vol. 2020, pp. 1–15, Mar. 2020, doi: 10.1155/2020/2353901.
[16] M. N. Azghandi, A. A. Shojaei, S. Toosi, and H. Lotfi, "Optimal reconfiguration of distribution network feeders considering electrical vehicles and distributed generators," *Evolutionary Intelligence*, vol. 16, no. 1, pp. 49–66, 2023, doi: 10.1007/s12065-021-00641-7.
[17] K. S. Sambaiah and T. Jayabarathi, "Optimal reconfiguration of distribution network in presence of D-STATCOM and photovoltaic array using a metaheuristic algorithm," *European Journal of Electrical Engineering and Computer Science*, vol. 4, no. 5, Sep. 2020, doi: 10.24018/ejece.2020.4.5.244.
[18] V. Vai, S. Suk, R. Lorm, C. Chhlonh, S. Eng, and L. Bun, "Optimal reconfiguration in distribution systems with distributed generations based on modified sequential switch opening and exchange," *Applied Sciences*, vol. 11, no. 5, Feb. 2021, doi: 10.3390/app11052146.
[19] C. L. B. Silveira, A. Tabares, L. T. Faria, and J. F. Franco, "Mathematical optimization versus Metaheuristic techniques: A performance comparison for reconfiguration of distribution systems," *Electric Power Systems Research*, vol. 196, Jul. 2021, doi: 10.1016/j.epsr.2021.107272.
[20] D. T. Tran, P. T. Ha, H. D. Nguyen, and T. T. Nguyen, "Apply three metaheuristic algorithms for energy storage-based integrated power system to reduce generation cost," *Bulletin of Electrical Engineering and Informatics (BEEI)*, vol. 12, no. 2, pp. 633–641, Apr. 2023, doi: 10.11591/eei.v12i2.4544.
[21] H. M. Asgher, Y. M. Mohmad Hassim, R. Ghazali, and M. Aamir, "Improved grey wolf algorithm for optimization problems," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 22, no. 3, pp. 1573–1579, Jun. 2021, doi: 10.11591/ijeecs.v22.i3.pp1573-1579.
[22] H. Hardiansyah, "Dynamic economic emission dispatch using ant lion optimization," *Bulletin of Electrical Engineering and Informatics (BEEI)*, vol. 9, no. 1, pp. 12–20, Feb. 2020, doi: 10.11591/eei.v9i1.1664.
[23] V. M. Joy and S. Krishnakumar, "Modified artificial bee colony optimization algorithm for adaptive power scheduling in an isolated system," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 21, no. 2, pp. 1168–1175, 2020, doi: 10.11591/ijeecs.v21.i2.pp1168-1175.
[24] H. Amar, M. Rachid, and B. Abdelkrim, "The study of reducing the cost of investment in wind energy based on the cat swarm optimization with high reliability," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 18, no. 4, pp. 2245–2250, Aug. 2020, doi: 10.12928/TELKOMNIKA.V18I4.15046.
[25] D. L. Duan, X. D. Ling, X. Y. Wu, and B. Zhong, "Reconfiguration of distribution network for loss reduction and reliability improvement based on an enhanced genetic algorithm," *International Journal of Electrical Power and Energy Systems*, vol. 64, pp. 88–95, Jan. 2015, doi: 10.1016/j.ijepes.2014.07.036.
[26] H. Hizarci, O. Demirel, and B. E. Turkay, "Distribution network reconfiguration using time-varying acceleration coefficient assisted binary particle swarm optimization," *Engineering Science and Technology, an International Journal*, vol. 35, Nov. 2022, doi: 10.1016/j.jestch.2022.101230.
[27] N. Kanwar, N. Gupta, K. R. Niazi, and A. Swarnkar, "Optimal allocation of DGs and reconfiguration of radial distribution systems using an intelligent search-based TLBO," *Electric Power Components and Systems*, vol. 45, no. 5, pp. 476–490, Feb. 2017, doi: 10.1080/15325008.2016.1266714.
[28] A. Tandon and D. Saxena, "A comparative analysis of SPSO and BPSO for power loss minimization in distribution system using network reconfiguration," in *Proceedings of the International Conference on Innovative Applications of Computational Intelligence on Power, Energy and Controls with Their Impact on Humanity, CIPECH 2014*, Nov. 2014, pp. 226–232, doi: 10.1109/CIPECH.2014.7019093.

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